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Bottom-Up Modeling of Building Stock Dynamics

Investigating the Effect of Policy and Decisions on the Distribution of Energy and Climate Impacts in Building Stocks over Time

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“And that’s really the essence of programming. By the time you’ve sorted out a complicated idea into little steps that even a stupid machine can deal with, you’ve learned something about it yourself.”

(Douglas Adams, 1987)

ABSTRACT

In Europe, residential and commercial buildings are directly and indirectly responsible for approximately 30–40% of the overall energy demand and emitted greenhouse gas (GHG) emissions. A large share of these buildings was erected before minimum energy-efficiency standards were implemented, so they are energy- or carbon-inefficient. Therefore, buildings offer significant potential for energy efficiency and GHG reductions compared to the status quo. To exploit this potential at a large scale, we require targeted policy measures and strategies. Moreover, the feasibility and impact of these measures should be quantitatively assessed.

Building stock models (BSMs) have long been used to assess the current and future energy demand and GHG emissions of building stocks. The most common BSMs characterize building stocks based on archetype buildings, which are thought to represent large segments of the stock. Future development is then calculated using retrofit, demolition, and new construction rates. The increasing availability of disaggregated datasets—building registries, 3D city models, and energy performance certificates—has enabled building-specific BSMs that describe the status quo as an input to energy planning, primarily on the urban scale. Owing to the availability of building-level data, BSMs can be extended beyond policy advice and urban planning, to the assessment of large building portfolios. Thus far, the urban scale advances in building-specific BSMs have not been transferred to the national scale, where such datasets are often unavailable. Moreover, the focus on an increasingly detailed description of the existing stock has left approaches for modeling stock dynamics without much development. Therefore, they are still primarily modeled through exogenously assumed rates. As this approach ignores the influences of economic, environmental, and policy factors on stock development, it limits the applicability and reliability of the model results.

This thesis addresses these shortcomings and advances the modeling practices of BSMs. The thesis outlines the current state of BSM-related research, focusing on the modeling of stock dynamics in BSMs and related fields. The thesis and its appended papers then propose a methodology for further developing the modeling of national building stock in terms of building stock characterization through synthetic building stocks as well as stock dynamics through the use of agent-based modeling approach. Furthermore, the thesis extends BSM applications to the assessment of large building portfolios. By integrating a maintenance and renovation scheduling method, BSMs can be used to inform the strategic decision-making and planning of large building portfolios.

Applying decision-making theory and microeconomic theory, the developed agent-based building stock model (ABBSM) analyzes stock changes from the bottom up by modeling the adoption decisions of individual building agents on building retrofits and heating system technologies. By taking a disaggregated approach to the study of building stock dynamics, we can assess the heterogeneity in the energy usage and climate impact of the stock, and track their developments over time. Moreover, the ABBSM can analyze the effect of specific policies aimed at lowering the building stock energy and GHG emissions rather than assessing only the effect of structural changes in the stock. The developed ABBSM is validated on the historic development of the residential building stock of Switzerland. Thereby, showing, that the ABBSM adequately can reproduced the aggregated development patterns (namely, the retrofit activity, heating system adoption, and energy demand) by modeling the decision-making of individual building agents. The future stock development simulated by the model assesses various policies for decarbonizing the Swiss residential building stock. The results highlight the effectiveness of regulatory instruments to phase out fossil fuel-based heating systems, while also highlighting the usefulness of financial instruments to prepare the market and lessen the additional burden on building owners. They further suggest that to achieve GHG emission targets by 2050, the relevant policies need to be in place by 2025 to accommodate the long replacement cycles of building components and to avoid unwanted lock-in effects. The integration of maintenance and renovation planning methodologies in BSMs for large building portfolios highlights the benefits of strategic approaches to the planning of energy efficiency and GHG emission reduction measures through a lifecycle cost approach. It can thereby assist building owners in developing long-term strategies that reduce the energy demand and GHG emissions of their portfolios, and hence meet the national energy and climate goals.

Keywords: Building stock modeling, building stock dynamics, agent-based modeling, synthetic building stock, GHG emissions, energy efficiency, renewable energy

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Claudio

Göteborg, November 2019

LIST OF PUBLICATIONS

This Ph.D. thesis is based on the following appended papers:

Paper I: **Nägeli**, **C.,** Camarasa, C., Jakob, M., Catenazzi, G., Ostermeyer, Y. (2018) ‘Synthetic building stocks as a way to assess the energy demand and greenhouse gas emissions of national building stocks’, *Energy and Buildings*, 173, pp. 443–460. doi: 10.1016/j.enbuild.2018.05.055.

Paper II: **Nägeli**, **C.,** Jakob, M., Catenazzi, G., Ostermeyer, Y. (forthcoming) ‘Towards agent-based building stock modeling: Bottom-up modeling of long-term stock dynamics affecting the energy and climate impact of building stocks’, *submitted to Energy and Buildings (under review).*

Paper III: **Nägeli**, **C.,** Jakob, M., Catenazzi, G., Ostermeyer, Y. (forthcoming) ‘Policies to decarbonize the Swiss residential building stock: An agent-based building stock modeling assessment’, *submitted to Energy Policy (under review).*

Paper IV: **Nägeli, C.**, Farahani, A., Österbring, M., Dalenbäck, J.-O., Wallbaum, H. (2019) ‘A service-life cycle approach to maintenance and energy retrofit planning for building portfolios’, *Building and Environment*. Elsevier, 160(May), p. 106212. doi: 10.1016/j.buildenv.2019.106212.

Other related papers that were authored or co-authored by Claudio Nägeli are listed below:

Ostermeyer, Y., **Nägeli, C.**, Heeren, H., Wallbaum, H. (2017) ‘Building Inventory and Refurbishment Scenario Database Development for Switzerland’, *Journal of Industrial Ecology*, 00(0), pp. 1–14. doi: 10.1111/jiec.12616.

Gontia, P., **Nägeli, C.**, Rosado, L., Kalmykova, Y., Österbring, M. (2018) ‘Material-intensity database of residential buildings: A case-study of Sweden in the international context’, *Resources, Conservation and Recycling*. Elsevier, 130(November 2017), pp. 228–239. doi: 10.1016/j.resconrec.2017.11.022.

Österbring, M., **Nägeli**, **C.,** Camarasa, C., Thuvander, L., Wallbaum, H. (2019) ‘Prioritizing deep renovation for housing portfolios’, *Energy and Buildings*, 202. doi: 10.1016/j.enbuild.2019.109361.

Camarasa, C., **Nägeli**, **C.,** Ostermeyer, Y., Klippel, M., Botzler, S. (2019) 'Diffusion of energy efficiency technologies in European residential buildings: A bibliometric analysis', *Energy and Buildings*, p. 109339. doi: 10.1016/j.enbuild.2019.109339.

Nägeli, C., Jakob, M., Sunarjo, B., Catenazzi, G. (2015) 'A Building Specific , Economic Building Stock Model To Evaluate Energy Efficiency and Renewable Energy', in *Proceedings of CISBAT 2015*, pp. 877–882.

Nägeli, C., Jakob, M. and Sunarjo, B. (2016) 'Building Stock Modelling - A novel instrument for urban energy planning in the context of climate change', in *Proceedings of IEECB 2016*.

Nägeli, C., Ostermeyer, Y., Kharseh M., Kurkowska I., Wallbaum H. (2017) 'A Multidimensional Optimization Approach to Refurbishment Design on a Multi-Building Scale', in *Proceedings of WSBE Hong Kong 2017*.

Jakob, M., Wallbaum, H., Catenazzi, G., Martius, G., **Nägeli, C.,** Sunarjo, B. (2013) 'Spatial Building Stock Modelling to Assess Energy-Efficiency and Renewable Energy in an Urban Context', in *Proceedings of CISBAT 2013*, pp. 1047–1052.

Jakob, M., Catenazzi, G., Sunarjo, B., **Nägeli, C.,** Wallbaum, H., Ostermeyer, Y., (2019) 'CREATE: A toolbox to develop, implement and monitor advanced energy and climate goals and strategies', in *Proceedings of eceee summer study 2019*.

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LIST OF ACRONYMS

ABM	Agent-based model
ABBSM	Agent-based building stock model
BSM	Building stock model
CO_2-eq	CO_2-equivalent
DCM	Discrete choice model
EAC	Equivalent annual costs
EU	European Union
FOE	(Swiss) Federal office for energy
FOEN	(Swiss) Federal office for the environment
FOS	(Swiss) Federal office for statistics
GHG	Greenhouse gas emissions
GIS	Geographical information system
kWh	Kilowatt hour
MARS	Maintenance and renovation scheduling
MFA	Material flow analysis
MNL	Multinomial logit
RES	Renewable energy source
TWh	Terawatt hour
WTP	Willingness to pay

1 INTRODUCTION

1.1 Background

The need to curb global greenhouse gas (GHG) emissions, and hence limit climate change to a global average temperature increase of below 2°C, was highlighted in the 2015 Paris Agreement. To reach this target, all sectors must drastically reduce their energy consumptions and GHG emissions in the coming decades. European countries have jointly been among the first signatories of the Paris Agreement, and have committed to reduce their domestic GHG emissions by at least 40% from their 1990 levels by 2030, highlighting the countries' commitments to mitigating climate change (Lativa and European Commission, 2015).

In European countries, residential and commercial building stock accounts for approximately 36% of total GHG emissions (European Commission, 2017). Many of these buildings are older than 50 years (Economidou et al., 2011), whereas minimum energy-efficiency standards in many European countries were introduced only in the 1970s and 1980s following the oil crisis. Therefore, these older buildings are typically energy-inefficient and equipped with fossil fuel-based heating systems (Meijer, Itard and Sunikka-Blank, 2009). Accordingly, these buildings offer a significant potential for reducing energy demand and GHG emissions. Thus far, this potential has been only partially exploited, as the renovation rate of existing buildings remains low across Europe (Economidou et al., 2011). Moreover, due to the long lifetimes of buildings and building components, there is a serious risk for lock-in effects, as buildings being built and renovated today will probably not be renovated for decades thereafter (Lucon et al., 2014). Urgently addressing the energy and climate impacts of buildings is, therefore, crucial to meeting the long-term emission and energy reduction targets.

Although many building technologies exists to lower the energy demand and GHG emissions, long lifetimes, high investment costs of energy-efficiency measures, and other barriers result in renovation and retrofit rates below the targets set by European policy-makers (Economidou et al., 2011). Consequently, the typical renovation, demolition, and new construction rates in European countries are approximately 1% or lower (Meijer, Itard and Sunikka-Blank, 2009; Economidou et al., 2011). Owing to this slow diffusion and uptake of energy-efficient and low carbon technologies, it is difficult to reach intermediate GHG emission reduction targets for buildings.

On a European level, the EU has issued various policies to reduce the energy and climate impact of buildings and to achieve the stipulated reduction targets. Among these policies are the Energy Efficiency Directive (European Parliament, 2012) and the Energy Performance in Buildings Directive (European Parliament, 2010), which aim to achieve a highly energy-efficient and decarbonized building stock by 2050. Both directives have been implemented on a national level and have resulted in various regulatory (e.g., stricter building codes, minimum efficiency performance standards, renewable energy requirements), financial (e.g., energy/CO_2 tax, subsidies), and informative (e.g., energy performance certificates) policy instruments. Policy-makers in charge of these measures face the problems of tracking the impact of the implemented measures in terms of their combined and individual effects as well as assessing whether the development is on track to meet reduction targets. To resolve these problems, to check the progress of implemented measures, and to assess whether the measures should be adapted, ex-post and ex-ante assessments of the development of the building stock and its energy consumption and GHG emissions are needed. To this end, we must understand the building stock dynamics and their role in decreasing the energy demand of buildings and accelerating the decarbonization of the building stock. The complexity and long timeframe of this problem, reinforced by lack of data on the building stock and its temporal development, call for a model-based assessment.

Bottom-up building stock models (BSMs) have long been used for assessing the energy and climate impact of building stocks (Swan and Ugursal, 2009; Kavgic et al., 2010). BSMs assess the current and future energy demand and GHG emissions of the building stock by first characterizing the status quo of the building stock and then projecting the development of the stock and its energy demand by modeling various processes, such as new construction, building retrofits, and demolition of existing buildings. They thereby analyze the resulting diffusion of building technologies and energy-efficient measures into the stock. BSMs have been applied on transnational and national (McKenna et al., 2013; Mata, Sasic Kalagasidis and Johnsson, 2014; Sartori, Sandberg and Brattebø, 2016), urban (Mastrucci et al., 2014; Österbring et al., 2016) and district scale (Fonseca et al., 2016). On these various scales, they have been used for example to assess policy scenarios (Heeren et al., 2013; McKenna et al., 2013; Sandberg et al., 2017), to support energy planning (Reinhart and Cerezo Davila, 2016; Torabi Moghadam et al., 2017), and to evaluate retrofit options (Fonseca et al., 2016).

Recent developments in bottom-up BSM-related research have focused on data input, energy modeling techniques, and validation of the status quo results of the building stock, typically on the urban scale (Reinhart and Cerezo Davila, 2016). This development has been driven by widening access to building-specific data and by increasing computational capabilities. Comparatively little focus has been devoted to improving the modeling methods for stock dynamics to model changes in the stock over time. Consequently, techniques for modeling stock dynamics and their application to different cases have fallen behind the advances made in other aspects of building stock modeling.

1.2 Thesis outline

1.2.1 Objective and research questions

The objective of this thesis is to advance the assessment of stock dynamics in building stock modeling. To this end, it will increase the model functionality and applicability of modeling approaches to better assess the long-term effects of stock dynamics on the level and distribution of the energy and climate impacts of building stocks, accounting for the economic, policy, and technological developments in various applications.

In particular, this thesis aims to answer the following research questions:

1. How can the lack of microdata be overcome to model and assess the distribution of energy and climate impact in large building stocks?
2. How can long-term building stock dynamics and their energy and climate impacts be modeled bottom-up while accounting for economic, policy, and technological frame conditions?
3. How does the energy and climate impact of building stocks develop under different policy scenarios, and what are the implications of these scenarios on policy-making?
4. How can building stock modeling approaches be made applicable for long-term building portfolio management through the integration of maintenance and renovation planning methods?

1.2.2 Thesis structure

This thesis builds on an extensive literature review of building stock-related research in general, and of stock dynamics in particular. The literature review analyzes the current state of research in building stock modeling and provides insight into alternative approaches of modeling building stock dynamics. A conceptual methodology of building stock modeling is developed in parallel, and is implemented to address the above research questions. To showcase the resolution of the research questions, the implemented modeling approaches are validated in various applications.

The research questions are individually answered in the appended papers in the order of their listing (see List of publications). The applications and time frames of these papers are illustrated in Figure 1. Papers I, II, and IV develop the methods, and Paper III applies the model developed in Papers I and II. Papers I–III are targeted at policy-makers as a main target group beyond the research community, whereas Paper IV targets large building portfolio owners. Accordingly, the individual papers also focus on different cases. Papers I–III are based on data of the national building stock of Switzerland, and Paper IV analyzes a multifamily housing stock portfolio in Gothenburg, Sweden.

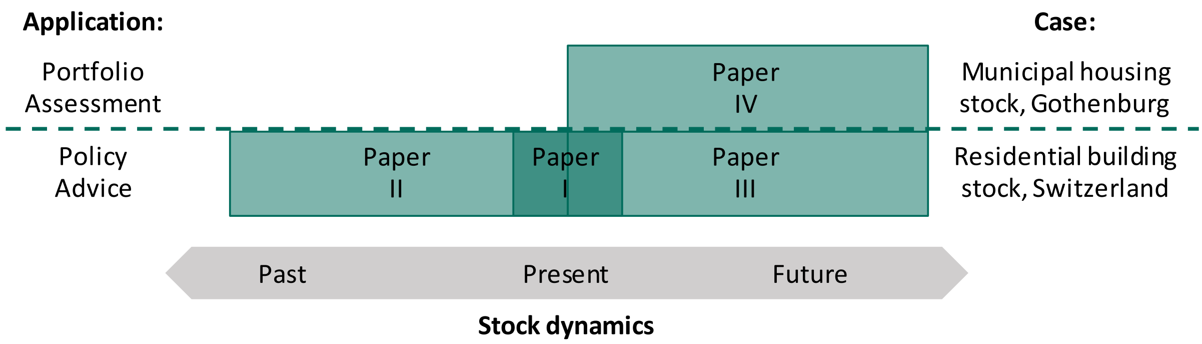


Figure 1 Thesis structure.

The thesis summarizes the research and the appended papers. Chapter 2 introduces the state of the research and context of the thesis. The different methodologies developed and applied in the thesis are described in Chapter 3. The results are presented in Chapter 4 and discussed in Chapter 5. Finally, Chapter 6 draws conclusions from the conducted research, and Chapter 7 provides an outlook on future research.

2 STATE OF RESEARCH

2.1 Building stock modeling

Research on the impact of building stocks has a long history, dating from large-scale housing surveys of state interventions in housing (Kohler and Hassler, 2002). Initially, this research collected knowledge on the state of the housing stock and the assessment of large-scale (social) housing programs. Currently, it has focused on the energy demand, building material use and waste, land use patterns, urban and regional planning, and the operational management of building stock (Kohler and Hassler, 2002; Kohler, Steadman, and Hassler, 2009). In particular, the energy demand of building stocks has been investigated through BSMs. Covering a wide range of model types and approaches, BSMs assess the energy demand and the related social, environmental, and economic impacts of building stocks.

The different BSM approaches can be broadly classified into top-down and bottom-up models (Swan and Ugursal, 2009). Top-down models operate on aggregate data and estimate the total energy demand of the building stock based on the aggregated characteristics of the entire stock. They are typically used to investigate connections between different sectors and the economy as a whole (Swan and Ugursal, 2009; Kavgic et al., 2010). In contrast, bottom-up models operate on the disaggregated level. They calculate the energy demand of individual buildings or groups of buildings and then extrapolate these results to the stock level (Swan and Ugursal, 2009; Kavgic et al., 2010).

Because they are built on aggregated data, top-down models are easier to set up and are usually less computationally demanding than bottom-up models. However, they are disadvantaged by their reliance on historical data and their inability to model (building) physical relationships; instead, they typically rely on statistical relationships, which can hardly model discontinuous technological advances such as technological breakthroughs. Therefore, top-down models are unsuitable for modeling technology-specific reduction potentials in the stock (Swan and Ugursal, 2009). Bottom-up models, on the other hand, are technology-specific and can more naturally model the effects of (technological) changes and the potential impact of related policies on the stock (Kavgic et al., 2010). Bottom-up models capture an increased level of detail, but at the cost of extensive data requirements, the modeler's know-how, and computational demand. Nevertheless, bottom-up BSMs have been increasingly applied in recent years, as the data have become more readily available and the computational power has increased (Kavgic et al., 2010; Reinhart and Cerezo Davila, 2016; Mastrucci, Marvuglia, et al., 2017).

Bottom-up BSMs are typically based on building physics and engineering principles or statistical models (Swan and Ugursal, 2009; Kavgic et al., 2010). Statistical models use statistical methods such as regression analysis or neural networks to match the energy consumption of buildings or a group of buildings to different attributes. Based on these relationships, they predict the energy demand of the entire stock. Similarly to top-down models, these models therefore rely on historical data (Swan and Ugursal, 2009). In contrast, engineering-based models use the building characteristics (the physical building data and their relationships) to calculate the energy demand based on heat transfer, thermodynamic principles, and building technology data. Depending on their input data, they can be further differentiated into population distribution models, archetype models, and sample-based models (Swan and Ugursal, 2009). Because engineering BSMs are based on the (building) physical principles, they can model new technologies with no historical consumption data. Accordingly, they are best suited for modeling the potential effects of such technologies on the building stock (Swan and Ugursal, 2009; Kavgic et al., 2010), and for assessing long-term stock developments and the effect of new technologies on those developments. Therefore, the following discussion will focus on engineering BSMs.

The following sections will describe bottom-up BSM modeling approaches in more detail, discussing the model applications, approaches to building stock characterization, and approaches to modeling building stock dynamics in BSMs and related research fields. The chapter will conclude with a brief summary of the main research gaps and trends addressed in this thesis.

2.2 Building stock model applications

Bottom-up BSMs have been developed and applied on various temporal and geographical scales and for different purposes. The geographical scale of BSMs can vary from transnational to national (McKenna et al., 2013; Mata, Sasic Kalagasidis, and Johnsson, 2014; Sartori, Sandberg, and Brattebø, 2016), to urban (Mastrucci et al., 2014; Österbring et al., 2016), and all the way down to the portfolio or district scale (Fonseca et al., 2016). Similarly, the temporal horizon ranges from status-quo analyses (Buffat et al., 2017) to long-term analyses of stock developments (Sandberg et al., 2017). Moffatt (2004) identified three types of BSM analyses with different time scales and geographical scopes: short-term investment analysis of small portfolios or areas (Fonseca et al., 2016), urban (energy) planning (Reinhart and Cerezo Davila, 2016; Torabi Moghadam et al., 2017), and policy analysis on a national or transnational scale (Heeren et al., 2013; McKenna et al., 2013; Sandberg et al., 2017). Therefore, depending on the intended application, bottom-up BSMs can be implemented using various methods which are broadly differentiable into two main types—static and dynamic—with different handlings of stock dynamics. Static methods can be further differentiated into models that assess building stock at a given point in time and models that compare the current state to a possible future state. Dynamic methods can model the stock evolution over time (Mastrucci, Marvuglia, et al., 2017). Based on these aspects, BSMs can be broadly classified according to Table 1.

Table 1 Bottom-up building stock model (BSM) classification based on model application, geographical scale, and temporal scale.

Model objective	Stock dynamics	Geographical scale	Temporal scale	Main application
Assessing the current state of the stock	Static	Portfolio, district, city, national, transnational	Status quo	(Urban) energy planning
Comparison between current and possible future state(s)	Static	Portfolio, district, city, national, transnational	Short-term	Retrofit/investment analysis
Scenario assessment of the building stocks over time	Dynamic	City, national, transnational	Long-term	Policy analysis

The first type of static models are designed to assess the state of the stock at a specific point in time. They are primarily used to map the current energy demand of buildings for energy planning and/or to identify improvement opportunities (Österbring et al., 2016; Reinhart and Cerezo Davila, 2016). For that purpose, they combine datasets and fill in the gaps in the existing data structure (Davila, Reinhart, and Bemis, 2016; Johansson, Olofsson, and Mangold, 2017). Depending on the spatial resolution, the energy demand can then be matched to (local) potentials for renewable energy generation. Moreover, the identified areas of high energy demand provide a reference for developing retrofit and other energy-efficiency strategies (see below), or can be used as input to the planning of energy infrastructures such as district heating networks (Delmastro, Mutani, and Schranz, 2016; Chambers et al., 2019). Such models are primarily applied on an urban or district scale, where such assessments are most useful (Moffatt, 2004), but they can also map the energy demand of buildings on the national scale (Buffat et al., 2017; Johansson, Olofsson, and Mangold, 2017).

The second type of static model compares the current state of the building stock with a possible future state(s). Such models are useful for assessing the effect of retrofit and other energy-efficiency measures (Fonseca et al., 2016), or for identifying investment opportunities in energy-efficient or renewable energy technologies (Mastrucci et al., 2015) in the building stock. Some of these models assess the techno-economic potential of fixed retrofit measures or packages of measures (Mata, Sasic Kalagasidis, and Johnsson, 2013); others optimize the combination of retrofit measures using multiple-objective optimization algorithms (Best, Flager, and Lepech, 2015; Fonseca et al., 2016). Such models are primarily used on small spatial scales (portfolio or district scales to the urban scale) because of their large computational demand. That said, optimization algorithms can also assess optimal retrofit options in representative building archetypes of a certain segment of the stock (Pietrobon et al., 2013). In these cases, the results do not directly support the development of retrofit or investment strategies for specific buildings; rather, they inform policy makers on which measures should be economically viable in a certain segment of the stock.

Dynamic BSMs model the development of building stocks over time by processes such as demolition, renovation, and new construction (Mastrucci, Marvuglia, et al., 2017). Therefore, these models are mainly used for studying the development of the energy demand and GHG emissions of building stocks in different scenarios (Mastrucci, Marvuglia, et al., 2017). As such, they are designed to inform policy-making, either directly by assessing the effectiveness of certain policy interventions (Kranzl et al., 2013), or indirectly by highlighting the effect of structural changes in the building stock on the energy demand and GHG emissions, and identifying the conditions under which the long-term reduction targets can be met (Heeren *et al.*, 2013; McKenna *et al.*, 2013; Sandberg *et al.*, 2017). Dynamic BSMs are primarily applied at the national scale (Heeren et al., 2013) or the transnational scale (Kranzl et al., 2013) to inform policy-making, but they are also used at the urban scale (Reyna and Chester, 2015). Other applications of dynamic BSMs beyond policy-making have not been extensively explored.

2.3 Building stock characterization

While bottom-up BSMs can describe and characterize building stocks in different ways: 1) archetype buildings, 2) sample buildings, or 3) individual buildings, in most BSMs, building stocks are characterized by archetype or sample-based approaches (Mata, Sasic Kalagasidis, and Johnsson, 2014). Both of these approaches use representative buildings for large segments of the building stock (typically segmented by building type, age, and/or size) (Moffatt, 2004). Building archetypes are artificially constructed building descriptions from data on previous construction standards and architectural descriptions of building practices. In contrast, sample-based models use a sample of existing buildings to represents the stock (Moffatt, 2004; Mata, Sasic Kalagasidis, and Johnsson, 2014). Both building archetypes and sample buildings are designed to represent an average building of a certain segment of the stock. Therefore, they do not reflect the full variation and heterogeneity of building sizes, types, and states in the building stock (Streicher et al., 2018). Moreover, the datasets from which building archetypes are constructed, such as the TABULA typology (TABULA, 2012), often neglect the previous retrofit measures applied to parts of the stock; therefore, they may not accurately characterize the stock segment they are meant to represent (Mata, Sasic Kalagasidis, and Johnsson, 2014). When previous measures are considered, their effect is averaged across the stock segment. This is problematic when assessing energy-efficiency measures, as it may lead to an over- or underestimate of future reduction potentials in the stock. In particular, the building energy demand is nonlinear, so if the assessment of the effect of an efficiency measure is based on the average building state, it may not reflect the average effect of the measure on the whole stock.

Recently, many BSMs for urban building stocks are being developed that forego the use of representative buildings, instead using and combining individual building microdata from different sources such as 3D building models, building registries, and/or data from energy performance certificates (Keirstead, Jennings, and Sivakumar, 2012; Reinhart and Cerezo Davila, 2016). As these models typically rely on data from a combination of these sources, dedicated data-matching and cleaning routines are being developed to combine these datasets using geographic information systems (GIS), usually based on address or midpoint coordinates, and impute missing data points (Davila, Reinhart and Bemis, 2016; Buffat et al., 2017; Johansson, Olofsson, and Mangold, 2017). Therefore, although micro-level datasets form the foundation of building-specific BSMs, they usually contain gaps that must be filled by archetypical data, especially, for the building physical and occupant-related data points (Reinhart and Cerezo Davila, 2016).

Wider access to building-level data—such as measured building-level energy consumption data—has opened new possibilities for calibrating and validating BSMs. Archetype and sample-based models are usually validated by aggregated energy statistics, which provide only an aggregate-level assessment. In contrast, building-specific BSMs can be validated at the individual building level using meter data or other energy consumption data. Studies carried out on building-level BSMs confirm their accuracy on the aggregate level, but the measured and calculated energy demand at the building level can widely vary, not least because the building stocks are modeled using archetypical data and standard occupant behavior (Reinhart and Cerezo Davila, 2016). These findings have inspired new assessments of data uncertainty and calibration methods for BSMs (Booth, Choudhary and Spiegelhalter, 2012; Cerezo et al., 2017; Mastrucci, Pérez-López, et al., 2017; Sokol, Cerezo Davila, and Reinhart, 2017). These studies usually assess the uncertainties in the occupant behavior and archetypal data. Some of these investigations have explored the general data uncertainty and quality, and their effects on the model reliability. Their methods also provide insight into the heterogeneity of the building stock in terms of occupant behaviors, building efficiency standards, and building geometry, as well as the effect of these parameters on energy demand (Mastrucci, Pérez-López, et al., 2017). Moreover, assessing the stock-level variation in occupant behavior can improve our understanding of the performance gaps[1] in building energy simulations, and the user influence on the energy demand in buildings (Majcen, Itard and Visscher, 2013; van den Brom, Meijer, and Visscher, 2018). This variation in the building stock is generally neglected in archetype or sample-based models, which characterize large segments of a stock by a single representative building with standard occupant and operational parameters.

Although national building-specific BSMs have been proposed (e.g., Buffat et al., 2017), the missing micro-level data (such as 3D building models) generally hinder the transfer of the advances attributable to building-level BSMs from the urban scale to a national scale. Consequently, national-scale modeling is still mainly based on building archetypes. Moreover, due to the high computational burden of modeling such a large

[1] The performance gap describes the discrepancy between the calculated energy demand based on standard user behavior and the actual (measured) energy consumption of buildings in practice (Majcen, Itard, and Visscher, 2013).

set of buildings in detail, building-level models usually assess only the status quo, and are rarely implemented with dynamic methods (Heeren and Hellweg, 2018).

2.4 Modeling building stock dynamics

There are many approaches to modeling dynamics in the building stock both in bottom-up BSMs and in other related modeling fields (e.g., technology diffusion, material flow analysis, or energy economy models). Mundaca et al. (2010) distinguished four categories of bottom-up energy economy models: 1) accounting, 2) simulation, 3) optimization, and 4) hybrid models. The differences, advantages, and disadvantages of models in these four categories are listed in Table 2.

The following sections describe the different modeling approaches in accounting and simulation models. The optimization models are excluded, as they are not directly relevant to the work of this thesis. Moreover, hybrid approaches are discussed only within the context of the accounting and simulation approaches, as they are typically built from one of these approaches.

2.4.1 Accounting models

Most of the traditional building stock models can be categorized as accounting models, because the stock changes are defined exogenously through demolition, new construction, and renovation rates (Sartori, Sandberg, and Brattebø, 2016; Mastrucci, Marvuglia, et al., 2017). For example, Heeren et al. (2013) model the evolution of the existing buildings based on retrofit rates differentiated according to the building construction period. Reyna and Chester (2015) do not model the retrofit of the existing stock but focus on demolition and new construction using a doubly constrained growth factor model, which models changes in the stock per time period based on the number of buildings entering and leaving the stock for each construction period. McKenna et al. (2013) use exogenously defined renovation probabilities for different retrofit depths based on a survey of building owners regarding their previous renovation behavior to model the implementation of retrofit measures over time.

In all of these studies, the stock dynamics are driven by exogenous inputs such as turnover or retrofit rates. In the best case scenario, these rates are based on historic data (in ex-post analyses) and are complemented by the modeler's assumptions (Heeren et al., 2013; McKenna et al., 2013). When developing future scenarios, the rates may also be based on expert judgments, as the retrofit and renovation activities are often tracked inconsistently (Economidou et al., 2011), potentially leading to unreasonably high retrofit or turnover rates (Sartori, Sandberg, and Brattebø, 2016). This uncertainty limits the usefulness and reliability of the model results, which significantly rely on a consistent exogeneous input (Mundaca et al., 2010). Moreover, if the stock dynamics are exogenously defined, the mechanisms inducing a change in the uptake of certain measures (e.g., subsidies or tax instruments that increase the retrofit rate) are not modeled explicitly, which limits the expressiveness of the model results.

Table 2 Modeling approaches for dynamics in bottom-up engineering models and their advantages and disadvantages according to Heaps (2002), Worrell, Ramesohl, and Boyd (2004), and Mundaca et al. (2010).

Approach	Description	Advantages	Disadvantages
Accounting	Accounting models primarily manage data and results. Unlike optimization and simulation models, they rely on the exogenous determination of technology choices and implementation rates.	▪ Simple, transparent, and flexible ▪ Low data requirements ▪ Can investigate issues beyond technology choice	▪ Heavily reliant on user input to develop realistic scenarios ▪ Does not automatically yield consistent results
Simulation	Simulation models provide a quantitative assessment of the development of the energy system. The dynamic behavior is modeled endogenously based on exogeneous drivers.	▪ Not limited to optimal/rational behavior ▪ Can account for different factors when modeling technology choice	▪ Tend to be complex and data-intensive ▪ Behavioral aspects can be controversial and difficult to parametrize ▪ Forecasts can be highly sensitive to initialization and parametrization of the model
Optimization	Optimization models seek the least-cost technology choices for energy systems under different technological, market, and policy constraints.	▪ Especially useful when many options exist ▪ Possible to back-cast from the desired future state	▪ Assumption of perfect competition and rational behavior ▪ Not suited to modeling real-world behavior ▪ Tends to yield extreme allocations, unless carefully constrained
Hybrid	Hybrid models merge the above modeling approaches. They also combine bottom-up and top-down methodologies.	▪ Can combine the advantages of different model types	▪ Often more complex than single models

2.4.2 Simulation models

Simulation models project the development by endogenously modeling the stock dynamics based on scenarios. However, the approaches on how to model stock dynamics in simulation models can vary significantly, depending on the purpose and scope of the model. This review describes the three kinds of models that informed the development of this thesis: 1) stock dynamics models, 2) energy economy models, and 3) agent-based technology adoption models.

2.4.2.1 Stock dynamics models

Stock dynamics models simulate the development of the building stock based on dynamic material flow analysis (MFA) (Hu et al., 2010; Müller, 2013; Pauliuk and Sj, 2013; Sartori, Sandberg, and Brattebø, 2016; Sandberg et al., 2017). These models simulate the development of the building stock by modeling the stocks and flows of buildings at the aggregate level. Whereas many BSMs focus on the energy consumption and climate impact of buildings, stock dynamic models are also used to assess the resource use of building stock through MFA (Müller, Bader and Baccini, 2004; Müller, 2005).

Sandberg et al. (2017)—as well as other applications of the same stock dynamics models (Sandberg, Sartori, and Brattebø, 2014; Sandberg et al., 2016; Sartori, Sandberg, and Brattebø, 2016)—simulated the development of the dwelling stock of Norway through functions describing the new construction, renovation, and demolition cycles of dwellings in the stock. The main drivers of the stock dynamics are the population development, floor area demand per person, building lifetimes (modeled by a survival function), and renovation cycles (Sartori, Sandberg, and Brattebø, 2016). Similar models have been developed for the Netherlands (Müller, 2005), China (Hu et al., 2010), and Switzerland (Müller, 2013).

As stock dynamics approaches operate in a top-down manner, they require relatively few input data. When the stock is segmented into clusters, it can be characterized by combining stock dynamics models with a bottom-up archetype model (Sandberg et al., 2017). However, the top-down nature of stock dynamics approaches is incompatible with the newer individual building-scale BSMs, which provide a discrete representation of each individual building. Moreover, stock dynamics models struggle to describe building-level processes and their interactions, as the stock description is based on a limited number of segments and building states. Therefore, renovation is typically defined as a comprehensive renovation only, without considering smaller component-based retrofits. Therefore, the full range of types and technologies (and efficiency standards) in real renovations is difficult to capture in stock dynamic models.

2.4.2.2 Energy economy models

Bottom-up energy economy models are numerous and wide-ranging. They can model the energy system as a whole (such as MARKAL and TIMES), in part (e.g., energy demand or supply), or in a specific sector (e.g., transport, residential, or industry). Therefore, BSMs overlap with energy economy models focusing on the energy demand of the building sector (residential and/or non-residential). Such energy economy models simulate the changing energy demand of the (residential) building sector by modeling the technology adoption by end-users (e.g., households or homeowners) through microeconomic principles (Sadler, 2003; Rivers and Jaccard, 2005; Giraudet, Guivarch, and Quirion, 2012; Kranzl et al., 2013; Müller, 2015). To simulate the stock dynamics, these models combine the turnover rates based on building or component lifetimes with discrete-choice methods such as the logit approach, to estimate the market shares of mutually exclusive alternatives (e.g., various heating system options) based on their calculated utilities (Train, 2003). The utility of these alternatives is typically evaluated by assessing the (discounted) lifecycle costs of the various technologies (Worrell, Ramesohl and Boyd, 2004). Attitudes and barriers to technology adoption can be considered both explicitly (e.g., through the restriction of certain options or through a willingness to pay for certain technologies, such as renewable energy sources), and implicitly (e.g., through an implicit discount rate) (Schleich *et al.*, 2016).

For example, using discrete-choice approaches, Sadler (2003), Rivers and Jaccard (2005), and Giraudet, Guivarch, and Quirion (2012) modeled the changes in market shares and the subsequent transition of building archetypes based on the changing technology costs and policy interventions. Similarly, the Invert/EE-Lab model simulates bottom-up investment decisions using the discrete-choice method (Kranzl et al., 2013; Müller, 2015). The model employs a two-stage decision process for individual building archetypes based on an estimate of the service life of different building components and a discrete-choice model (Müller, 2015).

Unlike the stock dynamics models described in the previous section, bottom-up energy economy models can model the endogenous changes in the stock by considering the costs, energy prices, and policy measures. By modeling the cost-based investment decisions of building owners, energy economy models can explicitly describe policy measures such as subsidies and taxes while simultaneously accounting for other barriers to diffusion, such as the availability and feasibility of certain technologies at the building level. Moreover, as decisions can be modeled on the building level, these modeling approaches are compatible with recent advances in building-specific BSMs. However, owing to their higher level of endogeneity and disaggregation, energy economy models are more complex than stock dynamics approaches, which increases their computational demand and calibration difficulty.

2.4.2.3 Agent-based technology adoption models

Agent-based models (ABMs) simulate complex systems in a bottom-up manner by representing various actors in a system as autonomous agents with different attributes, decision processes, learning abilities, and abilities to interact with each other and their environment (Railsback and Grimm, 2011). ABMs are especially suitable for complex multilevel problems with heterogeneous populations, because they describe overarching patterns through micro-level processes (Railsback and Grimm, 2011). The possibilities offered by the increasing availability of computational power have given rise to increased ABM use in many fields, ranging from ecology to social psychology (Railsback and Grimm, 2011). Moreover, they are more and more used to model technology adoption and diffusion by modeling individuals' adoption decisions (Peres, Müller and Mahajan, 2010). Because they represent decision-makers as individual agents, they offer a way to represent the heterogeneity of decision makers in technology adoption models by including different preferences and decision-making processes. Through ABMs it is therefore possible to operationalize psychological models of decision-making, such as the theory of planned behavior (Ajzen, 1991), and to integrate insights from behavioral economics, such as bounded rationality (Simon, 1955), in simulation models.

ABMs have already been used to model the adoption of energy-efficiency technologies in different realms (Kiesling et al., 2012; Zhang and Vorobeychik, 2017; Hesselink and Chappin, 2019), including the building sector (Knoeri, Binder and Althaus, 2011; Zhao, Ignacio J. and Augenbroe, 2011; Sopha, Klöckner, and Hertwich, 2013; Friege, 2016; Friege, Holtz, and Chappin, 2016; Busch et al., 2017). These studies simulated adoption decisions by various approaches, ranging from simple decision rules (e.g., contagion models in which agents adopt a technology as soon as an agent in their network adopts the technology) to sophisticated psychological and economic models based on the theory of planned behavior or microeconomic theory of individual choice behavior (Kiesling et al., 2012; Zhang and Vorobeychik, 2017; Hesselink and Chappin, 2019). The different ABMs prioritize various aspects of the technology adoption and diffusion process; for example, they may emphasize the importance of the decision process itself (Knoeri, Binder and Althaus, 2011; Busch et al., 2017), the spatial aspects of diffusion (Robinson and Rai, 2015; Busch et al., 2017), or the interactions between actors through social networks (Sopha, Klöckner, and Hertwich, 2011; Friege, Holtz, and Chappin, 2016).

These ABMs of technology adoption highlight the strength of ABMs in modeling the heterogeneity of adopters in terms of both their characteristics and their decision-making. Therefore, these models overcome the homogeneity assumption of traditional aggregate diffusion models and account for the heterogeneity in adopters (Kiesling et al., 2012). So far, the agent-based technology adoption models in the building sector often only examined a single technology type (e.g. heating systems), mostly with a focus on private homeowners or households as adopters rather than the technological change in a whole sector (Hesselink and Chappin, 2019). Moreover, the focus is on describing the adoption process of these technologies, rather than on investigating the effect they may have on lowering the GHG emissions and energy demand. Therefore, they often describe the decision-making process in great detail, but only rudimentarily model the effect of the building state on the adoption decision. This can, however, be addressed by integrating ABM techniques in building stock modeling in order to describe overarching stock dynamics by modeling processes such as retrofits and the replacement of components on the building level, taking into account the heterogeneity in the building stock.

2.5 Summary

After reviewing the recent developments related to building stock modeling, the following research trends and gaps, which this thesis aims to address, were identified:

- With the increasing availability of disaggregate data and increasing computational power, bottom-up BSMs have received more attention than top-down approaches.

- Thus far, BSM applications have focused on policy advice for national and regional policy-making and energy planning in cities and districts. Current modeling approaches are, therefore, also tailored to these applications and other applications of BSMs, such as the use of BSMs to assess the development of large building portfolios, have not been investigated as thoroughly.
- The possibilities offered by the increasing availability of geo-referenced building microdata and the inclusion of a GIS in BSMs have led to a focus on mostly urban building-specific BSMs. Although national building-specific BSMs exist, generally data availability and access remain a problem on that level. Therefore, national BSMs still mainly rely on aggregate archetype approaches, which may limit their explanatory power.
- The focus on building-specific BSMs has led to the development of increasingly detailed static BSMs that focus on the description of the status quo of the building stock. At the same time, dynamic BSMs have not developed as significantly. Modeling approaches for dynamic BSMs still rely mainly on exogenously defined rates or model stock dynamics from the top down.
- The use of exogenous rates to model stock dynamics limits the assessment of dynamic BSMs to structural changes in the stock and does not inform policy-makers of the effectiveness of policies aimed at lowering building stock energy demand and GHG emissions. Modeling approaches from energy economy models using discrete-choice modeling (DCM) as well as agent-based technology adoption models offer promising approaches to model stock dynamics in BSMs in order to address this issue, which will make it possible to take the heterogeneity in the building stock as well as different economic, policy, and technological frame conditions into account when modeling stock dynamics.

3 METHODOLOGY

This chapter summarizes the various methodologies developed and employed in the appended papers, and highlights the main methodological contributions. The chapter is organized into five sections describing the methodological elements of the thesis: 1) the method for characterizing building stock based on synthetic building stocks, 2) the agent-based building stock model (ABBSM) for simulating stock dynamics, 3) the method for assessing energy and GHG emissions, 4) the economic assessment methods, and 5) the extension of the BSM to enable maintenance and renovation planning.

3.1 Synthetic building stocks

The methodology for describing and characterizing building stocks through synthetic buildings relies on research on the generation of disaggregated synthetic populations of individuals and households based on aggregate data (Beckman, Baggerly and McKay, 1996). Synthetic populations are microdatasets with a simplified representation of an actual population. They are generated artificially from aggregate distributions or sample data, and are widely used in microsimulations and agent-based models requiring micro-level data that are unavailable at the required level of detail (e.g., because of privacy protection). These methods can also be used to create synthetic microdata on building stocks, where the problem of missing microdata exists as well, in order to describe individual buildings and their usage. Synthetic building stocks can be generated at the individual building level (i.e., each synthetic building represents a single building in the stock) or as a representative sample of the actual stock. In this thesis and the appended papers, the synthetic data were created as a representative sample stock. A synthetic building stock lies midway between an individual building-level description of the building stock and the archetype buildings (see Figure 2). The use of synthetic building stocks allows BSMs to more adequately describe the heterogeneity of building stocks in building size, state, occupancy, and user influence as compared to archetype approaches, while still being applicable in data-poor cases (e.g., in applications on a national scale) or in other cases where data may be available only at an aggregate level.

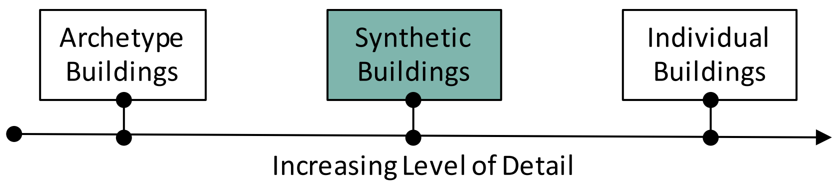


Figure 2 Synthetic building stocks in relation to other approaches of building stock characterization.

The methodology for characterizing the synthetic building stocks is developed and described in Paper I. Moreover, the initialization procedure of the ABBSM (see Section 3.2) in Papers II and III is based on the same methodology. The synthetic building stocks are generated in three steps (see Figure 3), which are further explained in the following sections.

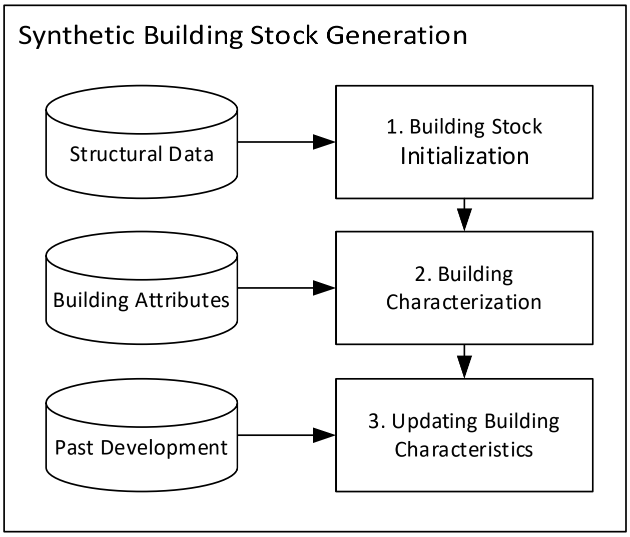


Figure 3 Process of generating a synthetic building stock (developed in Paper I).

The synthetic stock generation results in a microdataset of individual, synthetically created building records for the building stock modeling. Figure 4 illustrates the data structure of a synthetically created building from Paper I. The main attributes of a building are the building type and construction year, and the attributes defining the building geometry and size (e.g., floor area). These attributes are directly defined at the building scale. The different building components and technical systems of each building are then defined individually. Thus, each building comprises several building envelope components, a heating and hot water system, and a ventilation system (either natural or mechanical). Each of these technical components is described by its technical characteristics, and its installation or retrofit year. The internal area of the building is divided into various usage areas, which in residential buildings are the different dwellings. Each of the dwellings in multi-dwelling buildings is represented and characterized individually, reflecting the various possible dwelling sizes and occupancies in the building.

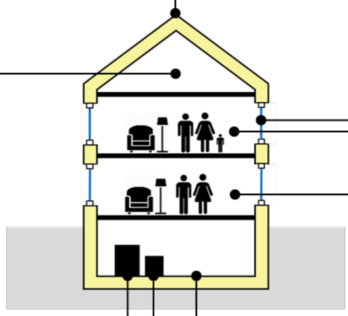
3.1.1 Building stock initialization

To initiate the synthetic building stock, the first step generates a representative sample differentiated by attributes such as building type, age, and/or location (e.g., climate zones). The representation is based on the structural data of the building stock, which describes the make-up (number of buildings or floor area) of the building stock. These data are typically available from national statistics, such as censuses and building registries. Each record in the sample represents a segment of the stock, and is defined through a scaling factor (in terms of the number of buildings) and a representative floor area. The result of step one is a data structure of individual building records that, when aggregated, represent the structural input data and can be further characterized in step two.

Building	
Building Type	MFH
Construction Period	1920-44
Construction Year	1931
Scaling Factor	159
Number of Dwellings	2
Residential Floor Area	166 m²
Heated Floor Area	201 m²
Footprint Area	100 m²
Volume	584 m³
Roof Type	Flat
Number of Floors	2
Number of Basement Floors	1
Height Floor	2.9 m
Length	17.2 m
Width	5.8 m
Ventilation Rate Infiltration	37 m³/h
Electricity Auxiliary	175 kWh/a
Heat Capacity	115 kJ/K m²

Opaque Components	
Component Type	Roof
Year	1992
Surface Area	152 m²
U-Value	0.4 W/m² K
Orientation	139°/319°
Angle	45°

Transparent Components	
Component Type	Window
Year	2001
Surface Area	25 m²
U-Value	1.4 W/m² K
g-Value	0.65
Shading Factor	0.81
Frame Ratio	0.18
Orientation	139°
Angle	90°



Usage: Dwelling	
Dwelling Area	83 m²
Number of Rooms	3
Number of Occupants	3
Occupancy Time	13 h/pers. day
Set Temperature	20.4 °C
Consumption Hot Water	31 m³/pers. day
Electricity Lighting	172 kWh/a
Electricity Appliances	1429 kWh/a

Heating System	
Heating System Type	Gas Boiler
Year	2006
Efficiency	96%
Energy Carrier	Gas
Solar Collector Installed	No

Hot Water System	
Hot Water System Type	Combined with HS
Year	2006
Efficiency	80%
Energy Carrier	Gas

Ventilation	
Ventilation Type	Natural
Year	-
Ventilation Rate	230 m³/h
Efficiency Heat Recovery	0%
Specific Fan Power	0 W/m² h

Figure 4 Representation of a typical synthetic building, including its building components, systems, and usage, (from Paper I).

3.1.2 Building characterization

The second step, building characterization, further differentiates the individual synthetic buildings generated in step one. To this end, it defines the various building attributes required for building stock modeling. These include the building geometry and the energy-relevant parameters (e.g., the original U-values). This step samples from distributions of the archetypical data on building attributes and/or sample data. The underlying data vary in their availability. They can be sourced from statistical offices, building standards, surveys on parts of the stock, and other reports. When the available data do not cover the distribution of a certain attribute across the entire or partial stock, the distributions can be constructed artificially from average values with a lower and upper bound. Normal or log-normal distributions can be selected for most continuous variables (e.g., U-values). The log-normal distribution is especially suitable for skewed distributions and for attributes that require a positive value. A uniform distribution can be chosen for selective attributes that do not cluster around the mean (e.g., building orientation). Lastly, discrete attributes (such as number of occupants) can be defined as a binominal distribution or based on discrete shares (e.g., shares of buildings with a basement).

3.1.3 Building updating

The third step continues the building characterization step. The building attributes are updated to represent their current state, accounting for the past retrofits, replacements, and other alterations. This step captures the changes in the existing stock that are not reflected in the data used for characterizing the building stock (e.g., the current U-value versus the U-value when the building component was originally built). The building update follows two stages:

1. For each building component whose state requires updating, the year of the last intervention is defined by sampling from the component lifetime distributions. For new buildings, this year will be the year of construction. For older buildings that have undergone one or more alterations in their lifetimes, the building components will have been reinstated, retrofitted, or replaced since the building was originally built.
2. If a measure has been implemented (i.e., if the year of the last intervention differs from the year of construction), the second stage assesses how the building component was altered. In the case of envelope components, one must first determine whether the component has been retrofitted (i.e., whether the energy efficiency has been improved) or reinstated without energy improvement. This decision is made through random choice based on the retrofit probability. The resulting efficiency improvement is related to the estimated year of implementing the measure.

The frequency of implemented measures in this step can be validated based on aggregated sales data (e.g., for windows or heating systems), sample data from surveys on past retrofitting and replacement activity, and/or component lifetime data.

3.2 Agent-based building stock modeling

A disaggregated discrete description of the building stock through synthetic building stocks (or individual buildings) offers new possibilities for ABM-based modeling of stock dynamics in BSM. The following sections describe an exemplary ABBSM, which is developed and validated based on historical data in Paper II, and is further applied to the modeling of future stock development in Paper III. The model is designed to support the study of the development of building stocks in terms of energy demand and GHG emissions, and in particular, how this development is influenced by decisions to retrofit the building envelope and replace the heating systems under different economic and technological frame conditions and policy interventions.

3.2.1 Model entities

The ABBSM differentiates between two main entities—building agents and the model environment—but more agent types (e.g., tenants or households) could be added. Building agents are developed from the same structure as the synthetic building stock (cf. Figure 4) and are extended to be used in the ABBSM. The characteristics of a building agent combine building attributes, including individual building components, building owner attributes (e.g., decision criteria) and location-specific attributes (e.g., availability of grid-bound energy carriers and renewable energy potentials). The latter two attribute types contribute to the behavior of the decision model to simulate building stock dynamics (see Section 3.2.3).

The model environment integrates the attributes of the climatic, economic, technological, and policy framework conditions. These parameters include the climate data in the energy calculation, the economic and technological characteristics of the modeled technologies for retrofits and new buildings (e.g., costs, efficiencies, and lifetimes of the building components and the heating and ventilation systems), the energy prices, the policy framework data (building standards, restrictions on the availability of technologies and subsidies), and other data driving the model behavior, such as population development data.

3.2.2 Model process

Figure 5 gives an overview over the model structure and process, which starts by initializing the model environment and the current state of the building agents. The building stock is initialized by the method that generates synthetic building stocks (see Section 3.1). After initialization, the model simulates the stock dynamics through the demolition, new construction, retrofitting, and replacement processes in time steps of one year. In each time step, the following three processes are executed:

1. Update the model environment: Based on the input data, the model environment is updated by adjusting the energy prices, costs of measures, and technology availability, as well as introducing new policy measures as defined in the model input.
2. Update existing buildings: The model loops over all building agents existing at the beginning of the time step, and updates their state. When a component or system in a building has reached the end of its lifetime, it is reinstated, retrofitted, or replaced based on the respective outcome of the decision model.
3. Generate new buildings: The final step adds new building agents based on the calculated demand for new construction. For each new building, it defines the individual building and component attributes, and chooses an initial heating system.

After updating its environment, the model sequentially updates all existing buildings. In the first step, each building is aged by one year. Based on the updated age, the scaling factor and representative floor area are reduced based on a survival function that accounts for the demolition of buildings represented by each building agent during that time step. The survival function is defined as a log-logistic function (see Equation (1)), which was calibrated on survival data from Aksözen et al. (2017) and Aksözen, Hassler, and Kohler (2017).

$$S(t,\alpha,\beta) = 1 - \frac{1}{1+\frac{t}{\alpha}^{-\beta}} \tag{1}$$

S: *Survival probability of the building*
t: *Lifetime of the building*
α, β:: *Scale and shape parameter*

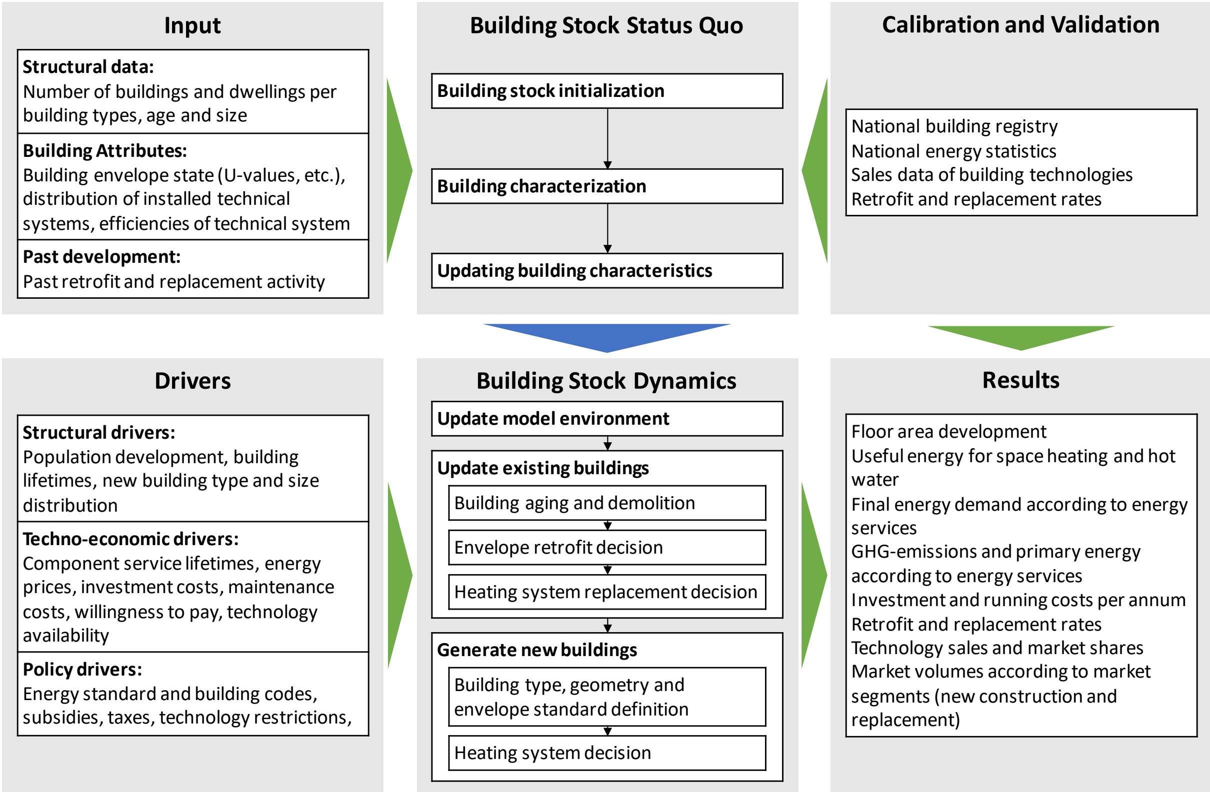


Figure 5 Process overview of the building stock initialization and stock dynamics in the agent-based BSM (ABBSM) developed in Paper II.

Afterwards, the individual building components are aged by one year as well. Each building component has an assigned maximum lifetime, after which it has to be reinstated, retrofitted, or replaced. The maximum lifetime is randomly sampled from a Weibull distribution (Equation (2)) when the agent is created or when a component has been replaced. The lifetime distribution of each component is based on data from IP BAU (1994) and Agethen et al. (2010). If a building envelope component or heating system has reached the end of its lifetime, the respective retrofit or replacement decision is triggered. Both the replacement decision of the heating system (installing the same system or switching to a different one) and the retrofitting decision of the building envelope (reinstating the component or implementing a retrofit measure) are simulated by the decision model described in Section 3.2.3 below.

$$
\begin{aligned}
F(t,k,\lambda) &= 1 - e^{-\left(\frac{t}{\lambda}\right)^k} \\
f(t,k,\lambda) &= \frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1} e^{-\left(\frac{t}{\lambda}\right)^k}
\end{aligned}
\tag{2}
$$

F: *Cumulative density function of the Weibull distribution*
f: *Probability density function of the Weibull distribution*
t: *Lifetime of the building component*
λ: *Scale parameter*
k: *Shape parameter*

Figure 6 illustrates an exemplary lifecycle of a building agent. The representativeness of the agent in the stock is adjusted yearly by the above procedure, and the building components are aged. When a component reaches the end of its lifetime, the respective decision is triggered. If the building agent decides to retrofit one of the building envelope components or replace the heating system, the energy demand, related GHG emissions, and energy costs of the building agent are adjusted by the integrated energy, GHG, and cost assessment module (see Sections 3.3 and 3.4).

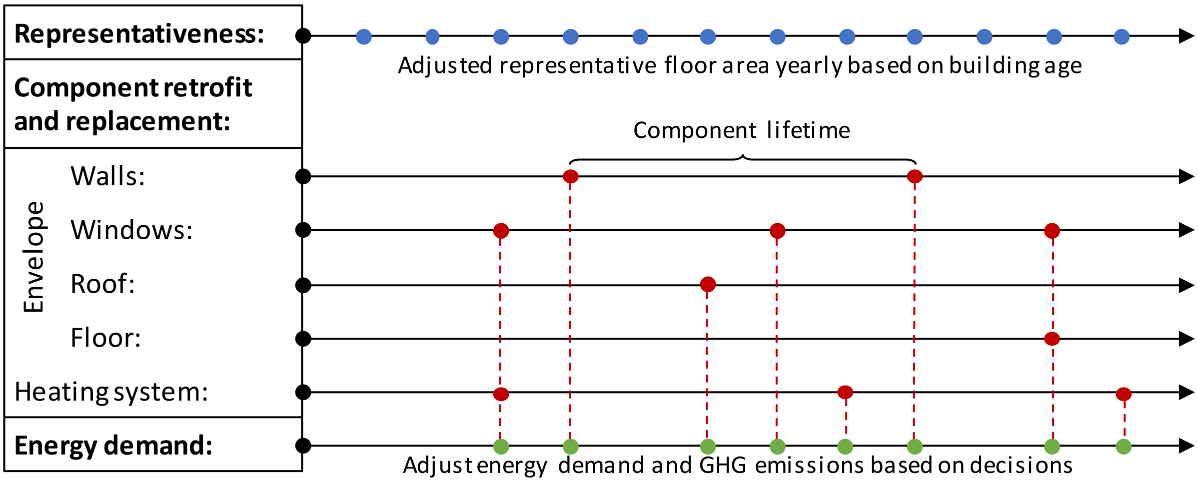


Figure 6 Representative lifecycle of a building agent, including different processes resulting in a change in the building state. Blue dots represent the updates of scaling factor and representative floor area, red dots represent the retrofit or replacement decisions, and green dots represent the updates of energy demand and GHG emissions.

After all existing buildings have been updated, the model calculates the demand for new construction in a given time step based on the population development and the resulting demand for additional living space. To satisfy the demand for new construction in terms of number of new dwellings, the number of new building agents is determined as the ratio of number of buildings in the stock to the number of building agents. The new building agents are then characterized by a procedure similar to the initialization procedure of the building agents, which subsequently defines the various building attributes based on input distributions. This procedure first defines the building type, size, geometry, and building envelope standard. Afterwards, the heating system in each new building agent is chosen using the decision model described below. Finally, the characterization of the new building agent is completed by calculating the initial energy demand and the related GHG emissions and energy costs.

3.2.3 Decision model

The decision processes of the building agents in the ABBSM to retrofit building envelope components, replace heating systems, and choose heating systems in new buildings are simulated by a decision model. The general decision model that implements these decision instances is built on a general model of strategic decision-making (Mintzberg, Raisinghani, and Théorêt, 1976) and the diffusion of innovation theory (Rogers, 1995). The decision model is structured based on the three steps of

Mintzberg, Raisinghani, and Théorêt's (1976) model of strategic decision making: 1) Identification, 2) Development and 3) Selection (see Figure 7). Moreover, for the development and selection process, it applies the principle of bounded rationality (Simon, 1955) (in that it reduces the number of considered alternatives), and a discrete-choice model (DCM) to select one of the alternatives (Train, 2003). The three steps are summarized in the following subsections. The decision model itself is further detailed in Paper II and its supporting information.

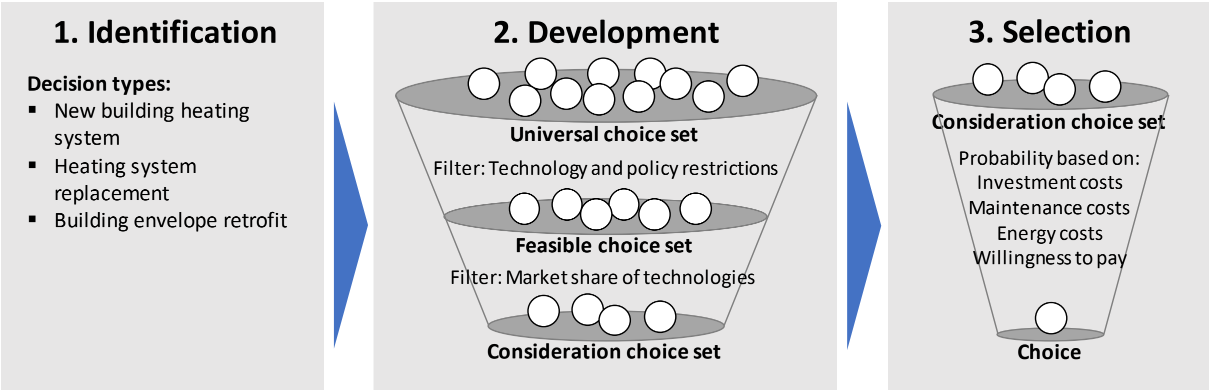


Figure 7 Overview of the general decision model applied in the ABBSM.

3.2.3.1 Identification

In the identification step, the building agent recognizes the need for a specific decision. The ABBSM differentiates among three decision types: 1) a new building heating system, 2) a heating system replacement, and 3) a building envelope retrofit. Each of these decisions is initiated by a distinct trigger. The heating system decision for a new building agents is triggered by the creation of a new agent, whereas decision types 2) and 3) are triggered when a component or heating system is reaching the end of its assigned maximum lifetime. Once a decision has been triggered, the choice set is developed in the next step.

3.2.3.2 Development

During the development step, the building agent constructs the choice set for the decision initiated in the identification step. The actual choice set is constructed from a universal choice set of each decision type, which includes all possible options. The choice set of a retrofit decision is directly formed from the universal choice set, which includes a reinstatement option (i.e., retaining the current level of energy efficiency) and three retrofit options with increasing levels of energy efficiency (e.g., three insulation thicknesses for a wall retrofit) depending on the retrofit standard of that time step. The level of energy efficiency (i.e., insulation thickness, U-values of windows) may change over the modeling period, reflecting the increasing retrofit standards imposed by technological progress and the tightening of codes and standards. The choice sets of the two decisions on heating systems is narrowed from the universal choice set in two steps. First, all inapplicable and unfeasible options for a certain building are excluded from the choice set by feasibility and policy filters (see Table 3). These options are further narrowed to a small consideration choice set by applying an aspect of the bounded rationality concept in assuming that not all possible options are considered in depth by the building owner (Lehmann *et al.*, 2017). Therefore, the model selects a restricted number of options that will be considered in depth by the building agent. First, the size of the considered choice set is defined by sampling from a gamma distribution, similar to the approach in de Haan, Mueller, and Scholz (2009); see Equation (3).

Table 3 Choice set restrictions on the various decision types.

Decision type	Restrictions
Envelope retrofit	None
Heating system replacement	Location-based restriction of unavailable heating system options (e.g., gas, district heating, and ground and groundwater source heat pumps)
	Technical feasibility of certain options due to minimum or maximum power thresholds
	Exclusion of decentral heating options if the building already has a central heating system
	Building agents with district heating only consider options that include district heating (i.e., no disconnection from heating grid)
	Building agents connected to gas grid do not consider switching to oil
	Building agents with a heat pump do not consider switching to a fossil-fuel heating system
	Building agents with solar collectors only consider options that include solar collectors
	Exclusion of options that are restricted by policy interventions (e.g., a ban on direct electric heating systems)
New heating system	Location-based restriction of unavailable heating system options (e.g., gas, district heating, and ground and groundwater source heat pumps)
	Technical feasibility of certain options due to minimum or maximum power thresholds
	Exclusion of options that are restricted by policy interventions (e.g., a ban on direct electric heating systems)
	Exclusion of options that do not meet the new construction standard (e.g., renewable energy source (RES) requirements)

$$p(n, \alpha, \theta) = \frac{1}{\Gamma(\alpha)\theta^{\alpha}} e^{-\frac{n}{\theta}} n^{\alpha-1} \tag{3}$$

n: *Number of choices in the choice set*
α: *Shape parameter*
Θ: *Scale parameter*

Second, the composition of the choice set is selected by weighted random sampling of the remaining feasible options. The weights of the options are based on the market shares of the technologies in the option; see Equation (4). However, in the replacement decision of the heating system, the currently installed system is always included in the choice set unless it is no longer available due to policy interventions (e.g., a ban on direct electric heating systems).

$$P_{ni} = \frac{e^{\sum w_{mn} MS_{mi}}}{\sum_j^S e^{\sum w_{mn} MS_{mj}}} \tag{4}$$

P_{ni}: Probability of option i being included in the consideration choice set of decision-maker n
w_{mn}: Weight of technology m for decision-maker n
MS_{mi}: Market share of technology m, which is part of option i

3.2.3.3 Selection

In the third step, the building agent evaluates each option in the consideration choice set and finally decides which option to choose. This stage of the agent's decision-making process is simulated by a DCM. DCM approaches are based on microeconomic utility theory. The applied DCM method is a multinomial logit (MNL) model, which is the most commonly applied discrete-choice model (Train, 2003). The MNL model calculates the probability of the decision-maker making a certain choice based on a utility function and the assumption of independence from irrelevant alternatives (Train, 2003). Hence, the choice probability depends on the observed part of the utility (i.e., what can be observed and measured by the model) and is calculated by Equation (5). The option is then randomly selected based on its calculated probability in the choice set.

$$P_i = \frac{e^{V_i}}{\sum_j^S e^{V_j}} \tag{5}$$

P_i: Choice probability of option i
V_i: Observed utility of option i

The utility of a given option is calculated by assessing the total (lifecycle) costs of the option (see Equation (6). To be able to apply the same utility function for any building size without unwanted scale effects, the model converts the total costs to specific cost per m^2 of floor area. Moreover, to ensure that the investment costs are comparable to the recurring costs—such as energy or maintenance and operation costs—the investment costs are converted to equivalent annual investment costs (see Section 3.4). Subsidies for various technologies and retrofit options are considered to reduce the investment costs. A possible energy or CO_2 tax will change the energy price, which, together with the energy demand of the building, determines the energy costs of each option. The willingness to pay (WTP) reflects additional attributes of a technology not covered by the other factors (e.g., increased comfort through new windows and preferences for a certain technology option) and is calculated based on a percentage of the equivalent annual investment costs.

$$V_i = \beta_{AC}EAC_{I,i} + \beta_{MC}C_{M,i} + \beta_{EC}C_{E,i} + \beta_{WTP}WTP_i \quad (6)$$

$EAC_{I,i}$: *Specific equivalent annual investment costs of option i*
$C_{M,i}$: *Specific operation and maintenance costs of option i*
$C_{E,i}$: *Specific energy costs of option i*
WTP_i: *Willingness to pay for option i*
β_n *Weighting factor for decision criteria n*

3.3 Energy and GHG emission assessment

The model includes an integrated energy and GHG emission assessment model that simulates the energy demand of the buildings in the stock. It also assesses the effect of the retrofit and replacement measures in the applications of the ABBSM's decision model (see above) as well as in the maintenance and renovation planning method (see Section 3.5). The overall energy calculation is based on the structure illustrated in Figure 8, which calculates the energy demand at different system boundaries (useful, delivered, final, primary energy, and GHG emissions). The model differentiates the energy demand and GHG emissions of various energy services such as space heating, hot water, ventilation, appliances, lighting, and auxiliary building services. The assessment module was developed in Paper I and applied in Papers II–IV. The model is further detailed in the Appendix of Paper I and in the supporting information of Paper II.

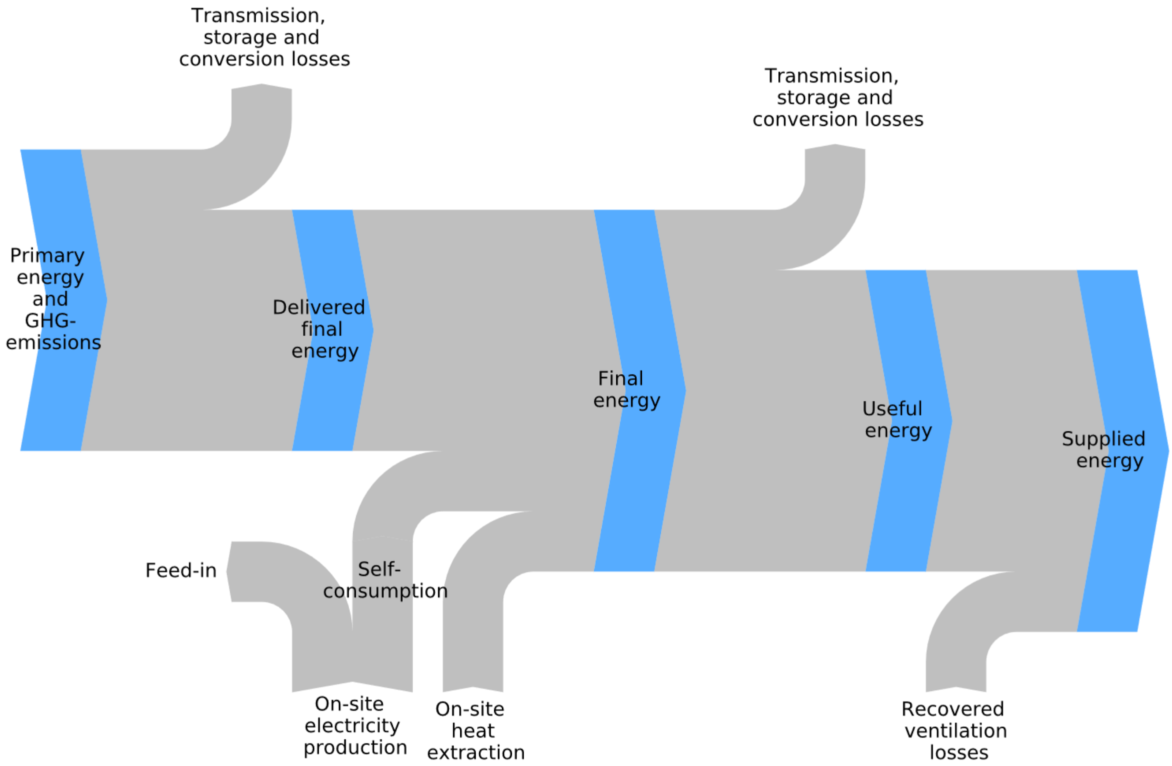


Figure 8 System boundaries of the energy and GHG assessment model.

The useful energy demand includes the useful energy for space heating and hot water. The calculated demand for space heating is based on the monthly steady-state energy balance method according to the norm ISO EN 52016-1 (ISO, 2017). The model is extended by a methodology that accounts for the performance gap and the (generally) notably lower indoor temperature in inefficient buildings compared to newer energy-efficient buildings, which affects the energy consumption of the building (Loga, Großklos, and Knissel, 2003; Majcen, Itard and Visscher, 2013). The method developed by Loga, Großklos, and Knissel (2003), therefore, adjusts the indoor temperature based on the energy-efficiency standard of the building. The useful energy demand for hot water, based on the number of occupants and the per person hot water consumption, is calculated for each dwelling and aggregated to the building level.

The final energy demand is based on the useful energy demand and is differentiated by the various energy services and the employed energy carrier. The final energy demand for space heating, hot water, and ventilation is calculated based on the useful energy demand and the heating and ventilation systems installed in the building, and their efficiencies. The efficiencies of space heating and hot water differ because the two energy services have different temperature levels and losses in distribution and storage within the building. Solar thermal collectors are assessed separately based on a monthly energy balance of the theoretically possible production and the actual demand for hot water and/or space heating in the building. Additionally, the electricity demand for appliances and lighting in the building is based on the number of occupants and the size of the dwellings in the building.

The delivered final energy demand excludes the final energy provided from the on-site heat extraction, such as the ambient heat from heat pumps and solar heat. On-site electricity production is included in Figure 8 for completeness, but is currently not part of the model because the on-site electricity-producing technologies (e.g., photovoltaic or combined heat and power) are excluded from the model. The model primarily uses the delivered final energy demand but the total final energy (including solar and ambient heat) is used for reporting and comparisons with official energy statistics.

From the final energy demand, the primary energy demand (total, non-renewable and renewable) and GHG emissions (total, direct and indirect) are then calculated based on the primary energy and emission factors of the various energy carriers.

3.4 Cost assessment

The model assesses the lifecycle costs of the building measures (new construction, reinstatement, retrofit, or replacement) of the building envelope components and technical systems. The costs include the investment, maintenance, operation, and energy costs of these technologies. The resulting costs are both an input to the decision model of the ABBSM as well as a model output (e.g., Paper III and IV).

The investment and maintenance costs of various measures are calculated based on a reference unit of each component (e.g., surface area for envelope components, nominal power for heating systems) and a cost factor according to Equation (7). The investment cost factors include the material and labor costs for a given measure. In the case of envelope components, cost factors are differentiated between reinstatement and retrofit measures per component. The latter is further differentiated based on different levels of energy efficiency (e.g., insulation thickness). Similarly, the cost factors for technical systems depend on the required size (e.g., nominal power for heating systems)—to take into account the nonlinearity of costs depending on the size of the system—and on the type of application (new construction, retrofit, or reinstatement). The model then interpolates between the different cost factors to obtain the appropriate level in a given building. In the case of the ABBSM, the model also considers subsidies for various technologies and retrofit options as a reduction in the investment costs.

$$C_{I,c,m} = c_{I,c,m} \cdot RU_c$$
$$C_{M,c,m} = c_{M,c,m} \cdot RU_c \tag{7}$$

$C_{I,c,m}$: *Investment costs of measure m on component c*
$c_{I,c,m}$: *Investment cost factor of measure m on component c*
$C_{M,c,m}$: *Maintenance and operation costs of measure m on component c*
$c_{M,c,m}$: *Maintenance and operation cost factor of measure m on component c*
RU_c: *Reference unit of component c*

The model converts the investment costs into equivalent annual costs (EAC) to make them comparable to the recurring costs such as the energy or maintenance and operation costs. The EAC of a given component is calculated from the investment costs based on a discount rate and the lifetime of the component according to Equation (8).

$$EAC_{I,c,m} = C_{I,c,m} \frac{r}{1-(1+r)^{-t_c}} \tag{8}$$

$EAC_{I,c}$: *Equivalent annual investment costs of measure m on component c*
$C_{I,c,m}$: *Investment costs of measure m on component c*
r: *Discount rate*
t_c: *Lifetime of component c*

The model calculates the energy costs from the energy price per carrier and the calculated final energy demand (Equation (9)). The energy prices, which are defined in the input data, vary over time and may include additional taxes (e.g., CO_2 tax) depending on the modeled scenario.

$$C_{E,ES} = \sum_{energy\ carrier} EP_{EC} \cdot E_{ES,EC} \tag{9}$$

$C_{E,ES}$ *Energy costs of energy service ES*
EP_{EC} *Energy price of energy carrier EC*
$E_{ES,EC}$ *Final energy demand for energy service ES of energy carrier EC*

3.5 Maintenance and renovation planning

In order to extend BSM application to purposes other than policy advice and energy planning, the BSM is developed to be used for strategic planning of large building portfolios. In this application, rather than simulating the decision behavior by the approach outlined in Section 3.2.3, the BSM is combined with the MARS method of Farahani, Wallbaum, and Dalenbäck (2019a) (see Figure 9) to plan and optimize the timing of maintenance and retrofit measures in the studied building portfolio.

The resulting BSM approach, developed in Paper IV, uses data on the existing state of a building portfolio and the techno-economic data on maintenance, reinstatement, and retrofit measures, including their costs and technological properties. Steps 2 and 3 of the synthetic building stock methodology fill the data gaps in the building portfolio data and calibrate the initial state of the buildings (Österbring *et al.*, 2019). Based on that input data, the method optimizes the maintenance and retrofit plan through an integrated cost, energy, and GHG emission assessment for different reinstatement or retrofit scenarios. Each scenario includes user-defined measures for retrofitting or reinstating the different building components at the ends of their lifetimes, and measures for maintaining the components during their lifetimes.

The MARS method optimizes the scheduling of the maintenance and renovation measures based on the deterioration of building components from a service-lifecycle cost perspective of each building in the portfolio (Farahani, Wallbaum and Dalenbäck, 2019a). From the resulting sequence of maintenance and retrofit measures, the model then projects the development of the energy, GHG emissions, and costs of the buildings in the portfolio using the procedures of building stock energy, GHG, and cost assessment outlined in Sections 3.3 and 3.4. In this way, the maintenance and renovation plans are individually developed for each building in the portfolio. These individual plans can then be aggregated to the portfolio level for assessing the development of the whole building portfolio. The result is a cost-optimized maintenance and retrofit plan for the entire building portfolio, which includes the projected development of the investment and energy costs, energy demand, and GHG emissions for different reinstatement or retrofit scenarios.

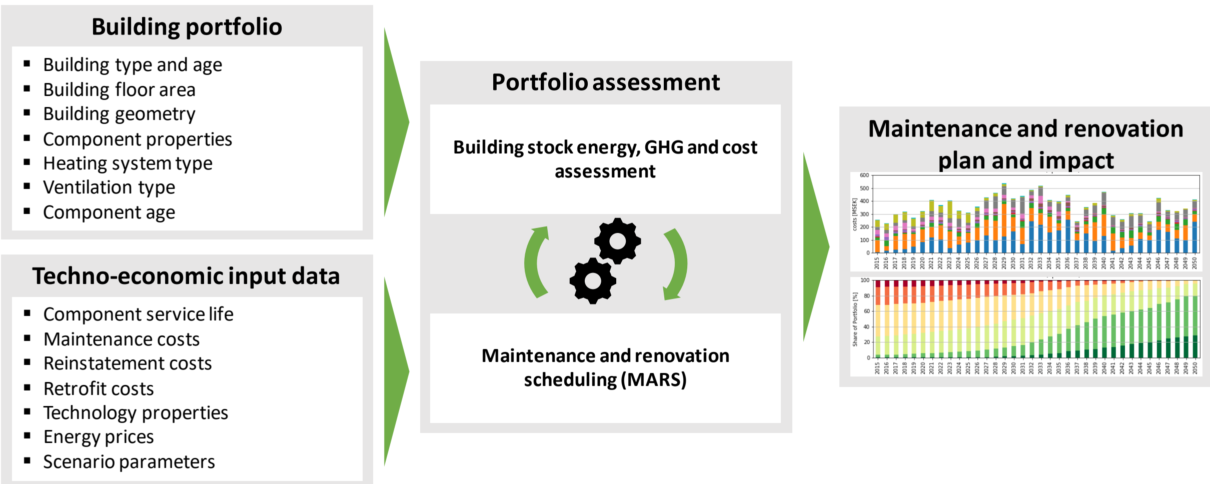


Figure 9 Overview of the integrated approach of building portfolio maintenance and renovation planning developed in Paper IV.

4 RESULTS

This chapter summarizes the main results of the appended papers. It relates the findings of the papers to the research questions and the overall goal of the thesis, thus highlighting the main theoretical and methodological contributions of the thesis.

4.1 Assessment of the status quo

Addressing the first research question, Paper I introduces a methodology that generates synthetic building stocks to overcome the lack of microdata when assessing the energy and climate impact of building stocks. In Paper I, the methodology is used to synthetically reconstruct a sample of 10,000 representative buildings of the Swiss residential building stock in 2015. The generated stock is then assessed based on the distribution of energy demand and GHG emission intensities in the stocky.

Figure 10 illustrates the distribution of the number of buildings and dwellings in the generated synthetic stock, and compares the results with the data used to generate the stock, which were sourced from the Swiss building and dwelling statistics (FOS, 2017a). The method adequately reproduces the distributions of the input data. The deviations are primarily caused by random sampling from the input dataset. The generated stock also matches the residential energy demand reported in the statistics (FOE, 2016) and the distribution of past retrofit measures in the stock (Jakob et al., 2014). Comparing the total final energy demand of the generated stock (67.2 TWh) with the national energy statistics (64.4 TWh), the method overestimates the demand by 4% overall, with slightly larger deviations for some energy carriers.

By analyzing the energy demand and GHG emissions of synthetic building stocks, we can investigate the distributions of these indicators in the stock (see Figure 11). The buildings equipped with a heat pump result in a clear peaks in the distributions of specific (delivered) final energy demand and GHG emissions, as they are more efficient than other heating system systems and the GHG intensity of electricity is low in Switzerland (KBOB, 2016). These causes are amplified by the higher share of heat pumps in newer buildings (with an above-average energy performance for space heating) than in older buildings. Furthermore, a notable share of wood-heated buildings and buildings connected to the district heating grid can be seen; these have lower specific GHG emissions compared with buildings heated by fossil-fuel systems. Fossil fuel-heated buildings with oil or gas boilers still account for 34% and 20% of the stock, respectively (see Figure 10), causing the second peak and long tail in the GHG emissions distribution.

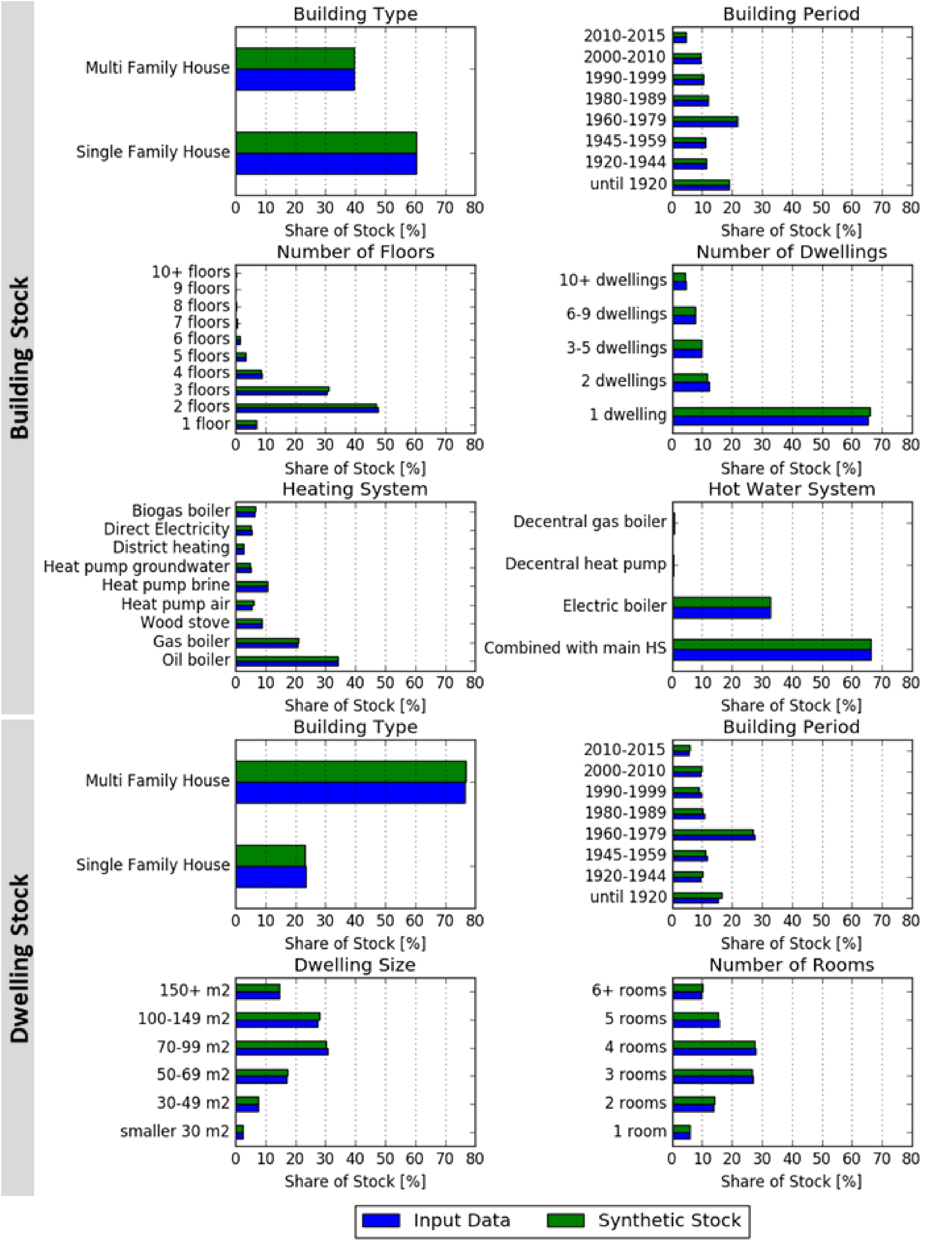


Figure 10 Distribution of various attributes across the created synthetic stock of buildings (top) and dwellings (bottom). Green and blue bars display the synthetic stock data and input data, respectively. The shares are weighted by the number of buildings/dwellings in the stock.

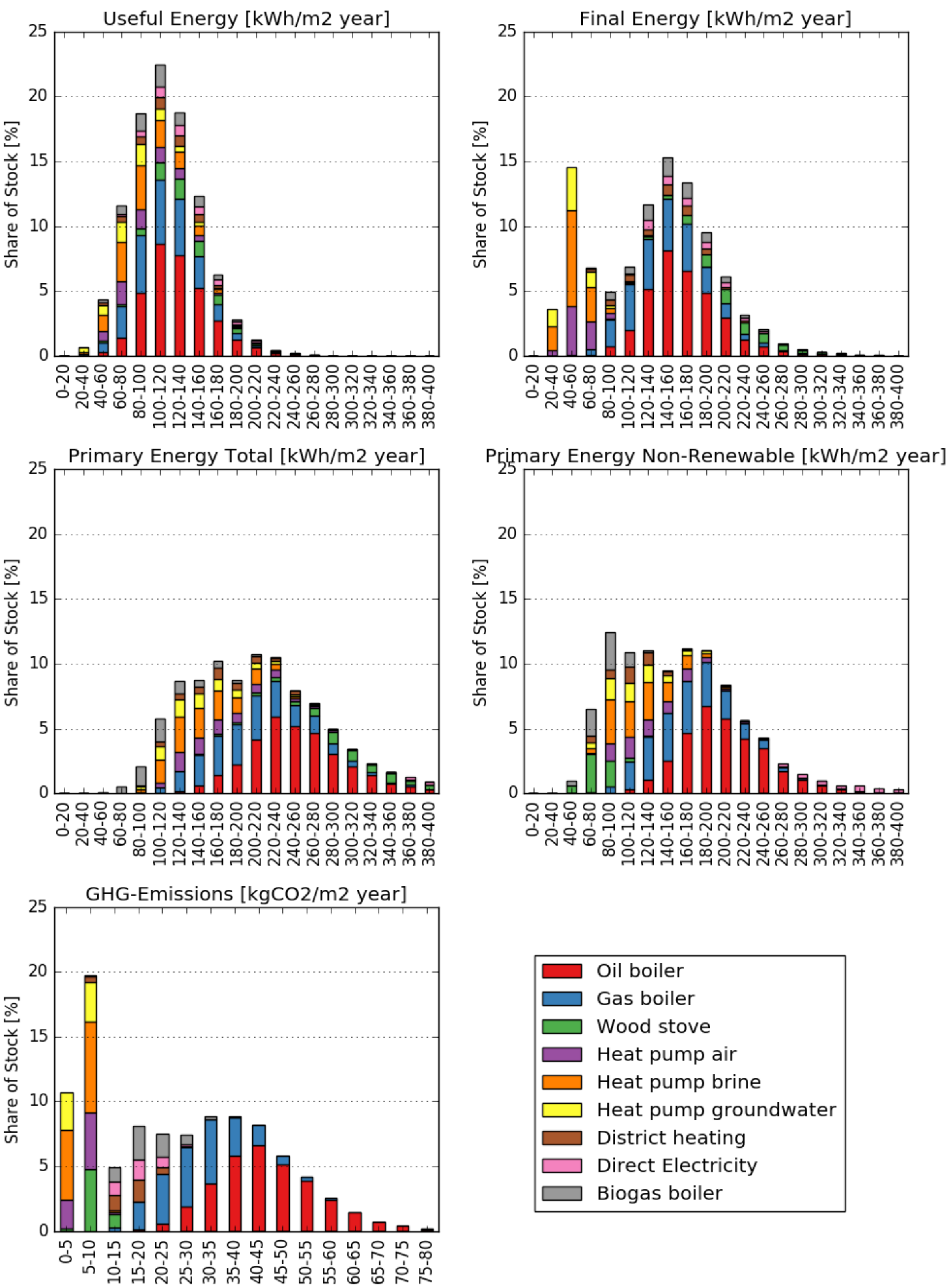


Figure 11 Distributions of specific useful energy (for space heating and hot water only), final energy, primary energy (total and non-renewable), and GHG emissions across the synthetic building stock, grouped by main heating system type. The shares are weighted by the representative floor area in the stock.

4.2 Ex-post assessment of the historic stock development

The use of synthetic building stocks to generate disaggregated building data makes it possible to utilize ABM techniques to model building stock dynamics to address the second research question. The developed ABBSM was applied to simulate the past development of the Swiss residential building stock from 2000 to 2017, as indicated in Paper II, to calibrate and validate the model.

The developed model was calibrated based on the retrofit activity between 2000 and 2010 (Jakob et al., 2014), and on the distributions of heating systems in the Swiss residential stock in 2000 and 2017 (FOS, 2004, 2017b). The calibrated model was then validated on additional data taken from the Swiss national energy statistics (FOE, 2018); see Figure 12. The model results match the aggregated energy demand with deviations of 2.8% to -1.6% over the modeling period. Moreover, as confirmed in the breakdown per energy carrier, the model largely reproduces the development of the Swiss household energy demand over the modeling period (see Figure 12). However, the model consistently over- and underestimates the demand for wood and gas, respectively, compared to the statistics. These deviations are mainly attributable to uncertainties in the model and the input data of the distribution (e.g., heating system distribution in the stock), use of the systems (e.g., use of wood-based heating may be reduced by the additional burden of operating the system), and efficiency of the different systems (e.g., overestimation of the deployment of condensing boilers), as well as potential uncertainties in the energy statistics.

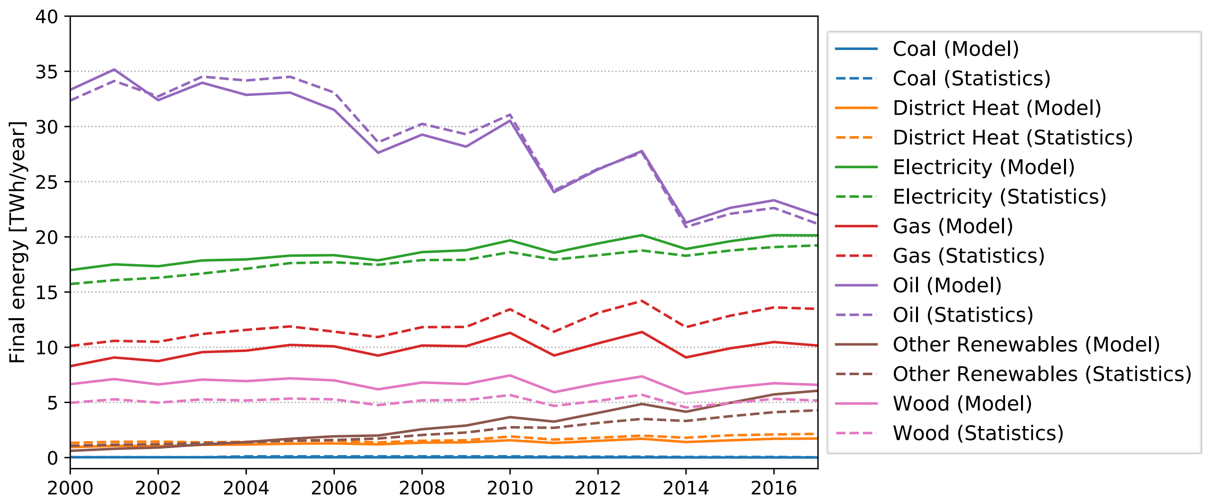


Figure 12 Development of the final energy demand of the residential building stock: comparison of model results (weather-adjusted) and household energy statistics (FOE, 2018).

Figure 13 compares the modeled retrofit activity with the reference data from Jakob et al. (2014). The model tends to underestimate the retrofit activity (i.e., the energy efficiency improvement of the components) and overestimate the pure reinstatement of components in some instances. This is most notable in the case of windows; especially, the share of retrofitted windows in multi-dwelling buildings is underestimated. The corresponding annual retrofit rates are highest for windows and flat roofs, ranging from 1.25% to 1.75% per year, and lowest for floors and walls, with below 0.5% per year.

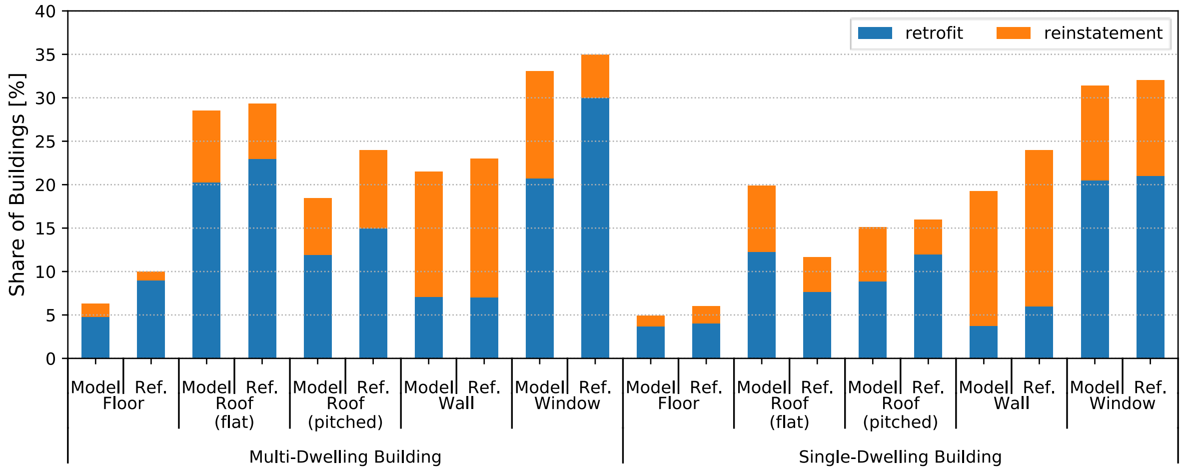


Figure 13 Comparison of retrofit activities and heating system shares of retrofitted and reinstated building components in the modeled building stock and the reference data from Jakob et al. (2014). Shares represent the implemented retrofits and reinstatements per building component in the stock built before 1990 and from 2000 to 2010.

The distributions of heating and hot water systems in the building stock during 2000 and 2017 are shown in Figure 14. The results are compared with the shares extracted from the 2000 Swiss census statistics (FOS, 2004) and the 2017 survey results of the office of statistics (FOS, 2017b). The slight deviations between the modeled stock and the reference data in 2000 are caused by random sampling for the stock initialization, and the differences arising from mapping the statistical information to the space heating and hot water system definition in the ABBSM. In 2017, the distributions of the modeled stock accurately match the statistics of both the space heating and hot water systems. There is, however, a slight underestimation in the share of oil and gas boilers, with an overestimation of the increase in heat pumps. The results indicate a clear shift from oil boilers and direct electric heating to heat pumps and gas heating systems, with smaller increases in district heating and solar hot water heating.

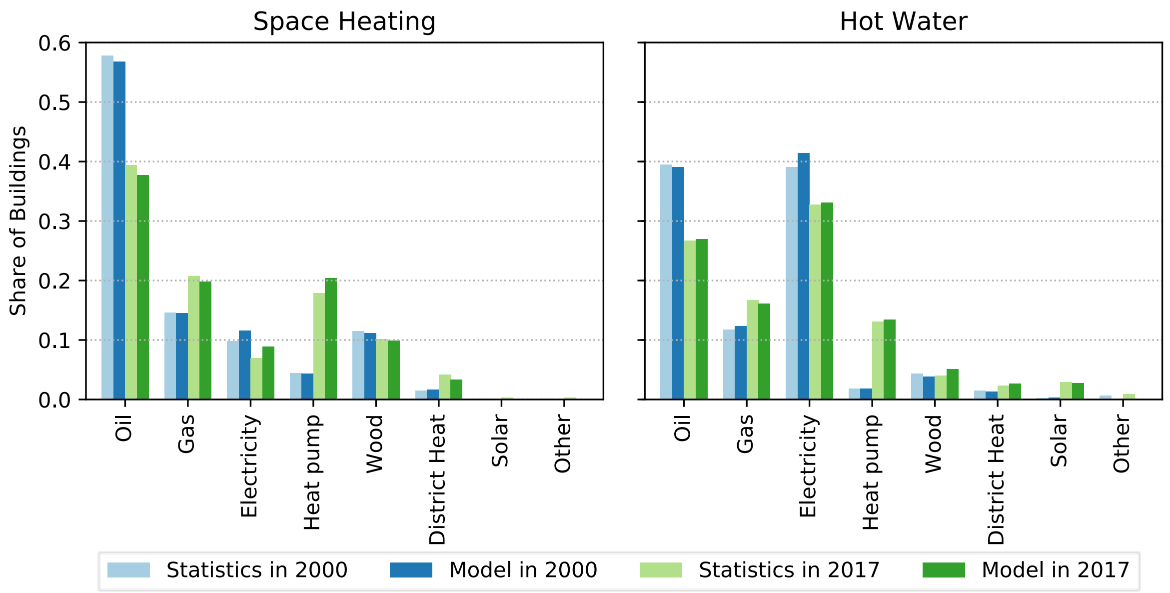


Figure 14 Distribution of heating systems and hot water systems in the building stock in 2000 and 2017: comparison of model results and statistics (FOS, 2004, 2017b).

The resulting development of key parameters in different segments of the stock during 2000 and 2017 is summarized in Figure 15. The distributions and medians of the U-values are notably shifted for roofs and windows, and more moderately shifted for walls and floors (which have a considerably lower retrofit rate than roofs and windows). The changing distribution of heating systems reflects the increasing replacement of oil boilers with gas boilers, heat pumps, and (to a lesser degree) district heating and wood-based heating systems in the existing buildings. The share of wood-based heating systems decreases in buildings from the earlier building periods, because older wood stoves are being replaced with newer heating systems of a different type. The efficiency gains in the stock, achieved through the new heating systems and building envelope retrofits, shifts the distributions of the delivered final energy demand and GHG emission intensities of buildings in the stock. The developing secondary peaks in the distributions of both indicators reflect the growing share of buildings equipped with heat pumps.

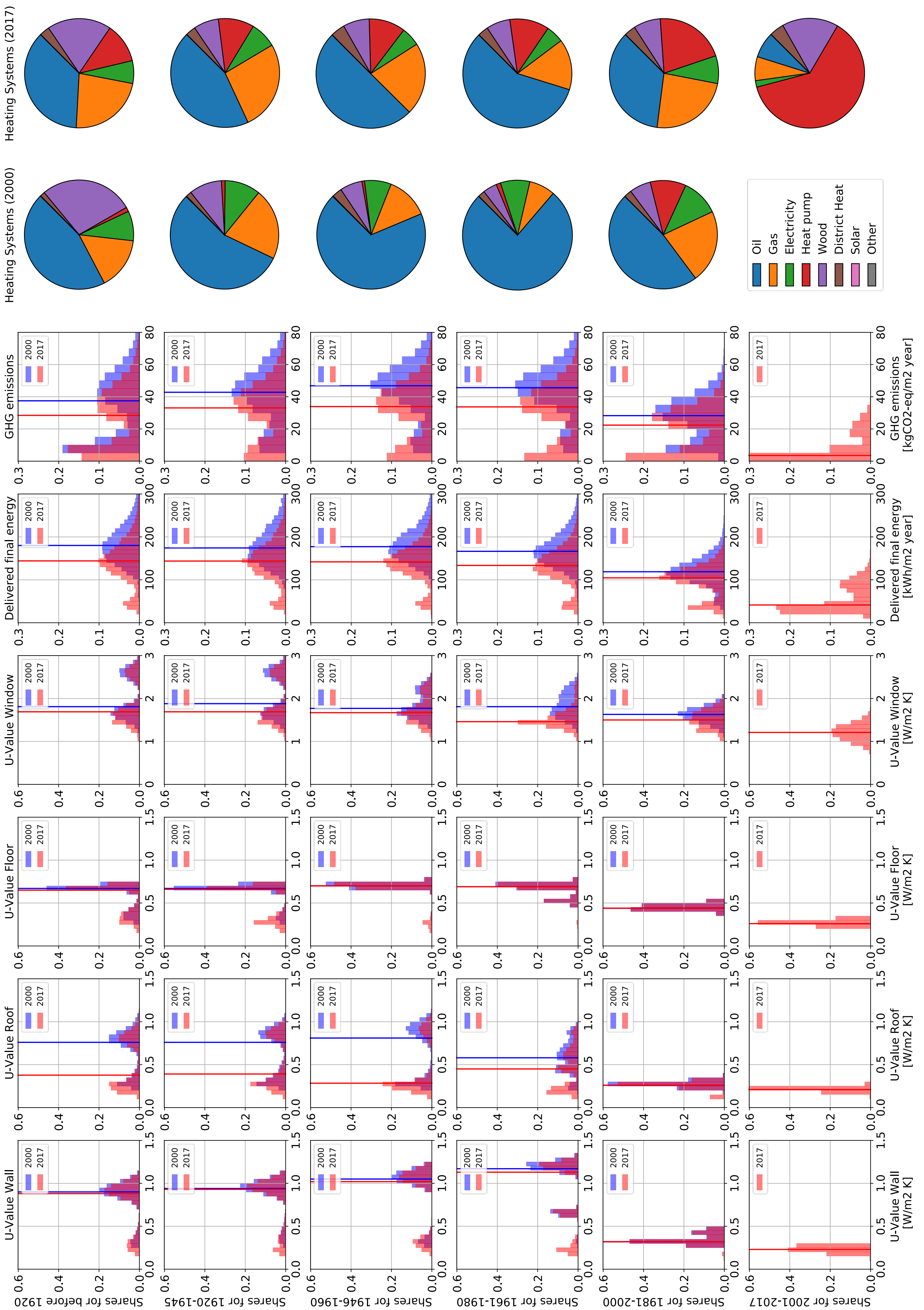


Figure 15 Distributions of key parameters and shares of heating systems in different age groups of the building stock in 2000 and 2017. Blue: stock in 2000, red: stock in 2017. Vertical lines indicate the median values of the stock segments.

4.3 Ex-ante assessment of future stock developments

To answer the third research question, the ABBSM developed in Paper II is used to model three scenarios for the development of the Swiss residential building stock until 2050 in Paper III. The modeled scenarios are as follows:

1. The reference scenario describes the development of the stock under the currently implemented and decided policy. Some trends and developments (e.g., energy price increase, population growth) are continued, but no new policies that address the climate impact of buildings are imposed.
2. The incentive scenario attempts to achieve the emission reduction targets by adding additional policies to the reference scenario. This scenario focuses on financial incentives, namely, a stepwise increase of the existing CO_2 tax on fuels and an extension of the subsidy program until 2030.
3. The regulation scenario extends the current policy framework, mainly by tightening the regulations. The proposed renewable energy source (RES) requirements are quickly imposed on existing buildings followed by the introduction of a GHG emissions limits for new and existing buildings in 2025. This limit will be stepwise reduced to zero until 2050.

The results of Paper III indicate that in all three scenarios, the total useful energy demand for space heating and hot water remains more or less constant despite significant growth of the building stock (+27% in heated floor area). The useful energy demand per floor area is reduced by continued building retrofits and the addition of efficient new buildings. The final energy demand and GHG emissions (both total and per floor area) are decreased in all scenarios, meaning that the growing stock is further offset by the efficiency gains and consequent decarbonization of the heat supplies. However, relative to the reference scenario, the final energy demand and GHG emissions are reduced by the additional policies in the regulation and incentive scenario.

Figure 16 shows the developments of the final energy demand of different energy carriers according to the different scenarios. Oil and gas, the main energy sources in 2017, decrease until 2050 in all three scenarios, while the use of electricity, district heating, and wood increases. In the reference scenario, the use of oil and gas is slowly reduced at an even rate over the entire period. In the incentive and regulation scenarios, oil and gas are phased out more quickly after the additional policies begin taking effect in 2020, but progress slows after 2040. By 2050, oil and gas are almost completely phased out in both scenarios, with demand reductions (relative to 2017) of -95% and -85% respectively in the incentive scenario and -98% and -95% respectively in the regulation scenario. Oil- and gas-based heating systems are primarily replaced by heat pumps, which can be seen in Figure 16 in the large increase in ambient heat use, and, to a lesser degree district heating, wood-based heating systems and solar collectors.

The overall reduction in final energy demand, especially the demand of oil and gas, reduces the GHG emissions of buildings in all three scenarios. In the reference scenario, the total and direct GHG emissions are reduced to 5.5 million tCO_2-eq and 4.1 million

tCO_2-eq in 2050, respectively, which does not meet the 80% reduction target from the 1990 levels. The regulation and incentive scenarios both meet the emission targets of 2030 and 2050. In 2050, the direct emissions of the regulation and incentive scenarios fall to 0.3 million and 0.7 million tCO_2-eq, respectively, and the total emissions decrease to 1.5 million and 2.0 million tCO_2-eq, respectively.

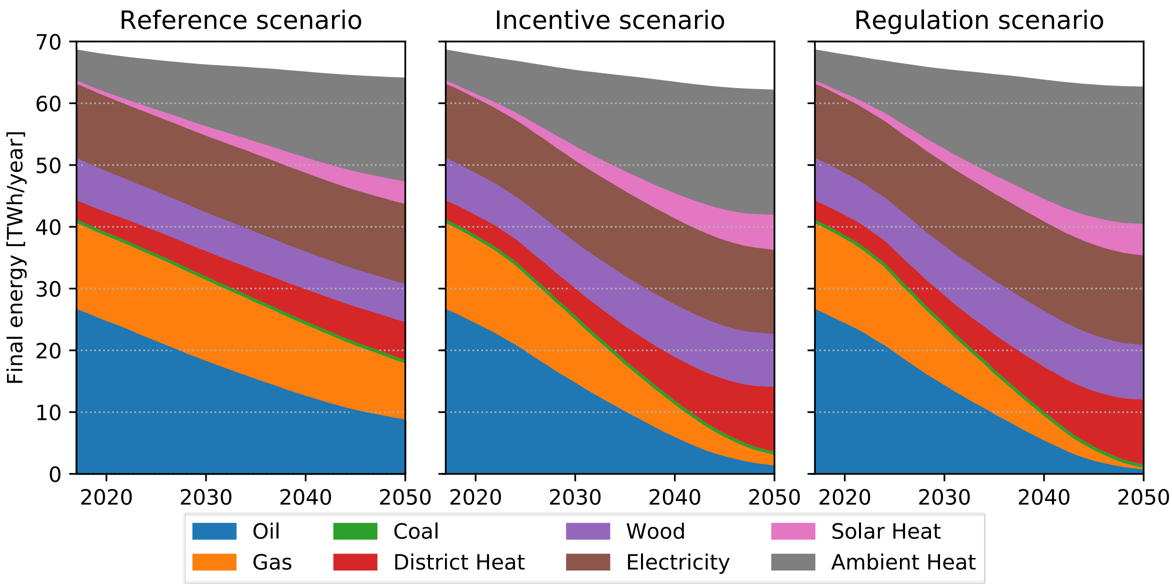


Figure 16 Development of the final energy demand of space heating, hot water, and auxiliary energy sources by different energy carriers in the three scenarios.

The declining GHG emissions of the Swiss residential building stock in the different scenarios are reflected in the development of the GHG emission intensities (including both direct and indirect emissions) in the stock (see Figure 17). In 2017, most of the stock emits more than 20 $kgCO_2$-eq/m^2 year, but buildings emitting below 5 $kgCO_2$-eq/m^2 year already comprise 20% of the total heated floor area. This share increases significantly under all three scenarios, as new buildings added to the stock primarily fall into that category. Moreover, the GHG emission intensity of existing buildings is reduced through building retrofits and the replacement of oil- and gas-based heating systems with renewable systems. In the reference scenario, the total floor area of buildings emitting more than 5 $kgCO_2$-eq/m^2 year falls to approximately 200 million m^2 in 2050. In the incentive and regulation scenarios, this share is further reduced by the imposed regulations, which increases the installation rate of heat pumps and (to a lesser degree) wood-based heating systems and district heating. A prerequisite of this development is the ongoing decarbonization of the electricity and district heating mix, whose carbon intensity is assumed to be further reduced under the scenarios.

Revenues from the CO_2 tax and subsidy expenditures in the three scenarios are plotted over time in Figure 18. The long-term revenue from the CO_2 tax decreases in all three scenarios as the oil and gas usage declines. However, the short- and medium-term revenues increase in the incentive scenario as the CO_2 tax rate is increased stepwise during that period, causing spikes in the CO_2 tax revenue. Moreover, each tax increase translates to a rise in the total energy costs of residential buildings. Although the tax revenue is reduced in the long run, the required subsidy expenditure increases with the growing market share of supported heating system technologies. Eventually, the revenue from the CO_2 tax no longer covers the subsidy expenditures in all three scenarios. This time point is reached earlier in the regulation scenario than in the reference and incentive scenarios, due to the fast decrease in oil and gas use without additional revenue from growth in the CO_2 tax. The additional regulatory requirements and possible cost reductions of RES technologies might eliminate the need for subsidies at this point.

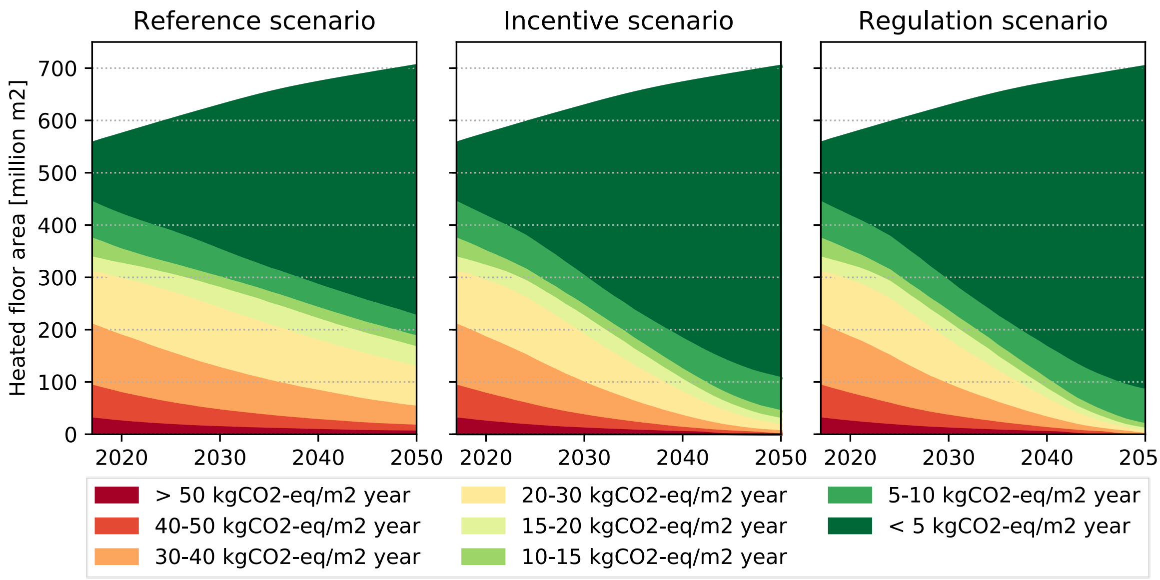


Figure 17 Development of the distribution of GHG emission intensities of the stock buildings in the three scenarios.

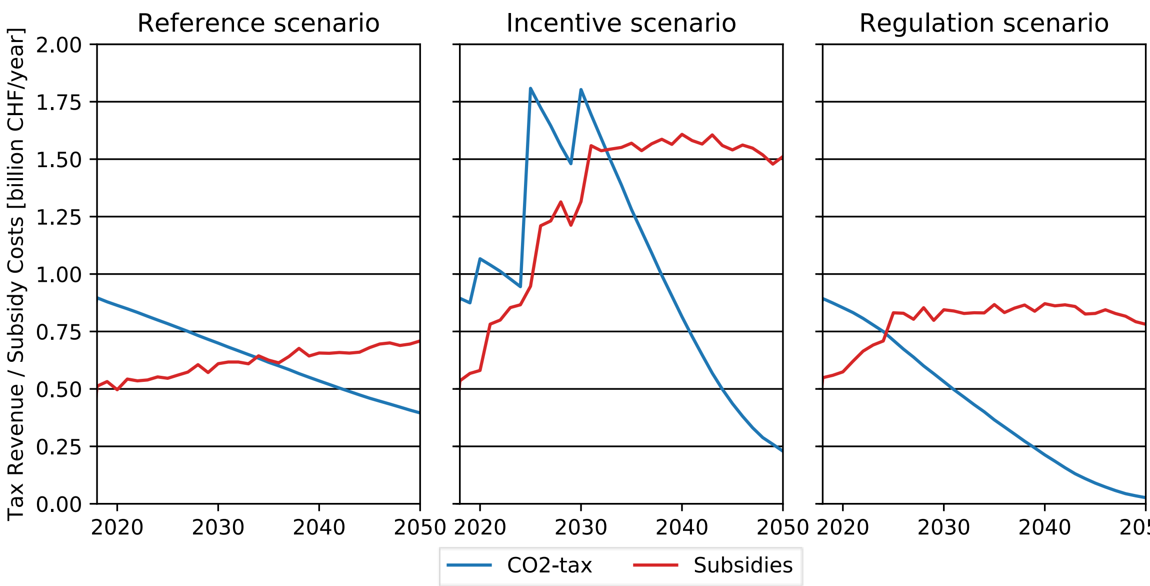


Figure 18 Development of the annual revenue of the CO_2 tax and public spending on subsidies for the three scenarios.

4.4 Portfolio planning for maintenance and renovation

In order to answer the fourth research question and to expand the applicability of BSMs for long-term building portfolio management, the BSM is combined with the MARS method for optimizing the scheduling of maintenance and renovation measures. In Paper IV, the model is applied to the building portfolio of the municipal housing company of Gothenburg, which includes more than 1,800 buildings. It is used to assess the effect of two scenarios: a reinstatement-only scenario and a retrofit scenario, which introduces ambitious retrofit measures for all major building components. Both scenarios are assessed based on two maintenance and renovation plans: 1) an industry plan with fixed maintenance and renovation intervals, according to industry standards (INCIT, 2017); and 2) an optimized plan, where maintenance and renovation intervals are optimized based on their lifecycle costs, according to the MARS method. For each of the plans for the two scenarios, the development of the energy demand, GHG emissions, and lifecycle costs of the building portfolio over time are assessed using the BSM.

The development of the energy intensities according to the different scenarios and plans (excluding the optimized plan for the reinstatement scenario) is illustrated in Figure 19. The distribution of energy intensities changes only marginally in the reinstatement scenario due to small efficiency gains from the reinstatement of building components and systems (e.g., by replacing the current heating system with a new one of the same type). In the retrofit scenario, the share of buildings with a low energy intensity increases significantly under both the industry and optimized plans. Overall, the retrofit scenario according to the industry plan leads to development of the average energy demand from 120.8 kWh/m^2 year to 68.4 kWh/m^2 year, resulting in a reduction of the total annual energy use by 320.7 GWh/year (-43.3%) by 2050. In the retrofit scenario according to the optimized plan, the average energy demand in the portfolio decreases even more to 65.0 kWh/m^2 year, resulting in a reduction in the total energy use of 340.6 GWh/year (-46.1%) by 2050. This larger reduction in the energy demand of the portfolio comes from the fact that retrofit measures are implemented earlier when optimizing the maintenance and retrofit schedule according to the MARS method. The lower total energy use in the optimized retrofit scenario is achieved at 5% lower lifecycle costs across the portfolio in terms of the equivalent annual costs compared to the retrofit scenario according to the industry plan and even 15% lower lifecycle costs compared to the industry reinstatement scenario. Moreover, comparing the lifecycle costs of the reinstatement scenario and the optimized retrofit scenario at the building level reveals that up to 77% of the buildings have a lower equivalent annual cost under the optimized retrofit scenario than under the reinstatement scenario. This means that these buildings can be retrofitted according to the measures specified in the retrofit scenario at lower lifecycle costs than seen with the reinstatement scenario. For the remaining 23% of the buildings, less ambitious retrofit measures may lead to a better result, or, since the portfolio also includes new and already retrofitted buildings, a reinstatement scenario might be the best option.

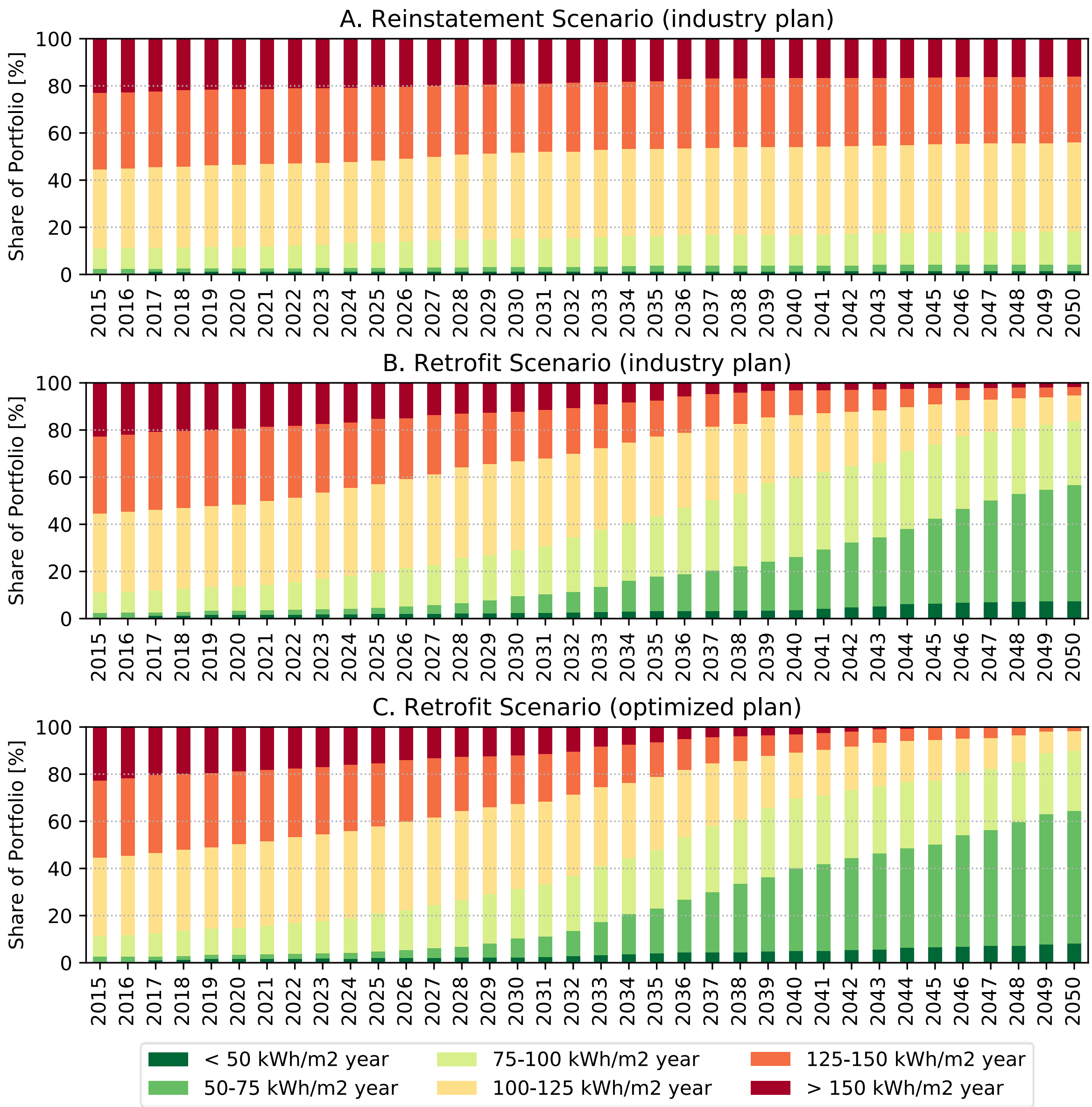


Figure 19 Development of the energy demand intensity distribution in the portfolio for the reinstatement scenario (A), the retrofit scenario based on the industry plan (B), and the retrofit scenario based on the optimized plan (C).

5 DISCUSSION

In the following chapter, the results are discussed in relation to the research questions and the overall goal of the thesis. Moreover, the contributions of the thesis are critically evaluated and assessed in relation to the existing literature and their scientific and practical relevance.

5.1 Addressing the research questions

Research question 1: How can the lack of microdata be overcome to model and assess the distribution of energy and climate impact in large building stocks?

The first research question is addressed through the methodological development of synthetic building stocks as shown in Paper I and applied in subsequent Papers. The results of Paper I indicate how, through the generation of a synthetic building stock, the heterogeneity of a building stock can be reconstructed in terms of its structure and the distribution of building characteristics, energy demand, and GHG emissions. Therefore, the results demonstrate how the assessment of synthetic building stocks can help shed light on the distribution of energy and GHG emissions in the stock. Previously, such an assessment was possible only through access to detailed microdata and is not possible through archetype-based BSMs. However, the developed methodology does not require more detailed data and builds upon data sources that are similar to those used in the archetype approach. Furthermore, the methodology allows to address the further research questions of this thesis by enabling the bottom-up modeling of stock dynamics in different applications that account for this heterogeneity.

Research question 2: How can long-term building stock dynamics and their energy and climate impacts be modeled bottom-up while accounting for economic, policy, and technological frame conditions?

The second research question is addressed in Paper II by developing an agent-based building stock model that models building stock dynamics in terms of new construction, demolition, retrofits, and replacements through decisions of disaggregated building agents. The developed model is calibrated and validated on the basis of the historical development of the Swiss residential building stock (as described in Paper II) and applied to simulate the future development of the stock (as described in Paper III). The results of Paper II reveal that the model can adequately reproduce different aggregate developments for structural changes, retrofit activity, heating system adoption, and energy demand in the stock. Furthermore, the results indicate how the use of disaggregated representative building agents makes it possible not only to assess results as an average over a building stock segment, but also to analyze the distribution of key parameters and results in the stock and track their development over time. Moreover, by differentiating various decision frames in the diffusion of heating systems (i.e., between the heating system in new buildings and the replacement of existing ones), the model accounts for the different diffusion dynamics between these segments. Furthermore, by modeling stock dynamics on the basis of individual decisions on the building level, the model can account for heterogeneity in the building stock (e.g., different building states and sizes), external driving, and restricting factors (e.g., availability of technologies and costs) in the adoption of building technologies. Thus, the results illustrate how the approach can be used to model the development of energy demand and GHG emissions of building stocks while accounting for a diverse set of policy measures, from regulatory (e.g., building codes and RES requirements) to financial (e.g., subsidies and taxes) instruments, along with changing economic (e.g., costs and energy prices) and technological (e.g., efficiency development) framework conditions.

Research question 3: How does the energy and climate impact of building stocks develop under different policy scenarios, and what are the implications of these scenarios on policy-making?

The third research question is addressed in Paper III by applying the developed ABBSM to model three scenarios for the development of the Swiss residential building stock. The results of Paper III indicate that while the current Swiss climate policy is effective in reducing energy demand and GHG emissions, the transition is too slow to reach the set reduction targets by 2050. The results of the incentive and regulation scenarios reveal that these reduction targets can only be reached by an almost complete phase-out of fossil-fuel heating systems by 2050, which in turn can only be achieved through the introduction of further financial and/or regulatory measures. The results indicate that financial incentives (e.g., increased CO_2 tax and subsidies) are an effective way to accelerate this transition. However, in the long run, revenues from the CO_2 tax will not be sufficient to cover the expenditures for the subsidy scheme because a decrease in oil and gas use also deflates revenues from the CO_2 tax. Therefore, regulatory requirements (e.g., RES requirements or a CO_2 limit for new and existing buildings) will be needed to completely phase out fossil-fuel heating systems while being able to reduce subsidy levels in the long run. Furthermore, the results reveal that long component lifetimes lead to low retrofit and replacement rates, which results in a slow transition of the stock. Thus, it is crucial that relevant regulatory policies are in place by 2025 at the latest to phase out fossil-fuel heating systems through their “natural” replacement cycle by 2050. Otherwise, more costly measures must be taken (e.g., replacement obligation for fossil-fuel heating systems) because systems and components need to be replaced before the end of their lifetimes, and measures cannot be implemented at marginal costs any longer.

Research question 4: How can building stock modeling approaches be made applicable for long-term building portfolio management through the integration of maintenance and renovation planning methods?

The fourth research question is addressed in Paper IV by combining the developed BSM with the MARS method for maintenance and renovation planning of buildings. Paper IV illustrates how the integration of the MARS method in BSM makes it possible to use BSMs for long-term strategic planning for building portfolios in terms of their energy, GHG emissions, and lifecycle costs. The results of the assessment of multiple maintenance and renovation scenarios for the example of the building portfolio of the municipal housing company in Gothenburg indicates how, through an optimized planning approach, ambitious retrofit measures can be implemented in the majority of buildings at lower lifecycle costs than those seen in the reinstatement scenario. Therefore, the results indicate the benefit of taking a strategic approach to planning for maintenance and renovation in building portfolios using building stock modeling.

5.2 Critical review

The methodological developments and results of this thesis advance building stock modeling practice in different ways with regard to building stock characterization, modeling building stock dynamics, and BSM applications.

The characterization of building stocks using synthetic building stocks improves building stock characterization methods compared to the generally used archetype approach. By generating numerous representative buildings to represent a certain stock segment instead of a single archetype, the model can more adequately represent the heterogeneity in the building stock. Moreover, the use of input distributions to characterize different building attributes increases the diversity of building states and types that can be represented in the synthetic stock compared to building archetypes. Furthermore, using synthetic building stocks, past retrofits and energy-efficiency measures can be represented as discrete representations in the synthetic stock and are not averaged out through the archetype characterization. This is especially important for assessing building stock segments with a long history of retrofits. Moreover, the correct accounting for previous measures has implications for the further assessment of building stocks such as when investigating the feasibility of retrofit and energy-efficiency strategies for various stock segments. Because of nonlinearities, the average of individual building results may not be equal to the results for an average situation represented by the archetype. Therefore, a synthetic building stock can provide a more accurate representation and more detailed understanding of the distribution of the energy demand and GHG emissions in the existing stock. For example, a synthetic building stock can identify the part of a stock segment that has already been (partially) addressed in terms of energy efficiency and the parts that still need (further) energy-efficiency improvements.

The implementation of the methodology to generate synthetic building stocks developed for the Swiss residential building stock, as applied in Paper I, has some limitations. While the methodology is specifically designed to overcome the lack of data (especially microdata) within the building stock, this does not mean that the implementation of the method cannot be improved by accessing better data. For instance, the combination of different datasets is primarily based on building type and age, which may lead to unrealistic combinations when generating synthetic buildings. For example, the random allocation of dwellings into buildings based on these criteria may lead to the unrealistic composition of dwellings within a building. While this issue can be addressed by restricting sampling and applying common-sense filters (e.g., restrictions on the size of the dwellings to be chosen), more detailed data on the composition of dwelling sizes within multi-dwelling buildings will greatly improve this part of the methodology. Moreover, the building characteristics sampled from different input distributions within the building characterization step are assumed to be largely independent of each other, while in reality, these characteristics may often be correlated with one another (e.g., U-values of different components). However, at a stock level, there are insufficient data on which building characteristics are correlated and to what degree. While a temporary solution may be to use assumptions to link attributes, additional epidemiological studies on building energy use and correlations between building characteristics may help fill in the gaps in the long run (Hamilton et al., 2013).

The methodology for generating synthetic building stocks lays the groundwork for the development of bottom-up modeling of building stock dynamics using agent-based modeling, as presented in Papers II and III. The use of ABM to model retrofit and replacement decisions on the building level makes it possible to consider the impact of factors (e.g., investment costs, energy prices, and technology availability) and policy measures (e.g., subsidies or renewable energy requirements) on these decisions. This allows to explicitly study the impact of regulatory and financial policy instruments on the development of the building stock through their effects on the decision-making of individual building agents. Moreover, by modeling decisions on the building level, the developed ABBSM considers interactions within the building between different retrofit and heating system decisions. For example, the order in which decisions on the heating system and building envelope retrofits are made by building agents affects the outcome because the effect of previous measures may influence the calculated utility and the choice probability of the following measures. For example, agents that first replace their heating system with an efficient heat pump will be less likely to subsequently retrofit their building envelope because these measures will become less financially attractive.

The main limitation of this approach lies in the difficulty of calibrating and validating the model behavior. While this is a general issue in agent-based modeling (Railsback and Grimm, 2011) and in other modeling fields, it is further complicated in BSM owing to the missing, incomplete, or inconsistent data on the stock development in terms of the composition, implemented building retrofits, and heating system adoption. Therefore, even though the model is conceptually based on the established theory of decision-making of building owners, the model can be only calibrated and validated in terms of its aggregate behavior, which increases the risk of overfitting. There are examples of more thorough empirically grounded ABMs (Sopha, Klöckner and Hertwich, 2013; Friege, 2016); however, they typically focus on a single technology group (e.g., heating systems) and/or types of adopters (e.g., households), which simplifies their bottom-up calibration. Nevertheless, such methods could be used to further develop the ABBSM approach in terms of its empirical foundation in the future. Therefore, a more detailed calibration and validation based on actual choice data or a detailed longitudinal dataset that tracks buildings over time may help improve the decision model and the underlying datasets. Furthermore, thus far, the ABBSM has primarily focused on the definition of building agents from a building energy demand and GHG emission assessment perspective, and the characterization is less detailed for building owner attributes. Therefore, the variation in building owner types, including how the decision-making processes may differ from one another, is currently not considered in the model. Differentiating agents in terms of owner types and/or decision strategies, such as in Sopha, Klöckner, and Hertwich (2013), would be a viable development to address this shortcoming. Furthermore, additional and different triggers of renovation and adoption decision processes (e.g., include the decision to renovate after the sale of a building, as in the model developed by Friege (2016)) can be included in the model at a later stage. However, the lack of a comprehensive overview and data on the processes and criteria of different owner types led to the development of this more simplified approach that can be used as a basis to develop the decision-making strategies of building agents in future studies.

The integration of a methodology for the strategic long-term planning of maintenance and renovation in BSMs, as presented in Paper IV, opens BSMs to a new application. This development makes it possible to use BSMs for the strategic planning of maintenance and renovation measures at the portfolio level from a lifecycle costs, energy, and GHG emissions perspective. Thereby, the portfolio-level BSM can be used for budget allocations and the efficient distribution of resources when planning the implementation of energy-efficiency measures over time. Because the implementation of the method in Paper IV used available national datasets, it is easily transferable to other building portfolios within Sweden without the need to collect extensive data to set up the model. However, the use of generic data to fill gaps has some drawbacks because this approach introduces uncertainties into the model (e.g., with regard to the current state of the buildings and the remaining lifetime of components). Therefore, these uncertainties should be addressed when operationalizing the model through regular inspection of the individual buildings in the portfolio to assess and track the current state of each building and its components. However, a sensitivity assessment performed on the building level of the maintenance and renovation approach reveals that the method is fairly insensitive to reasonable variations in most input parameters (e.g., the deterioration rate, discount rate, and energy savings) in terms of the timing of measures (Farahani, Wallbaum and Dalenbäck, 2019a, 2019b), which makes it feasible to perform an initial assessment of the portfolio on the basis of the generic data.

5.3 Implications of results

This thesis has several implications for science and practice regarding both its methodological contributions and the results of the studies.

5.3.1 Scientific implications

The scientific implications of the work described in this thesis primarily lie in the methodological developments that are described in the appended papers. The methodology for generating and modeling building stocks on the basis of synthetic building stocks, as presented in Paper I, advances modeling practice in terms of building stock characterization. Using synthetic building stocks, BSM-based assessments can move away from a study of building stocks that are based on averages to study the distribution and variability of results in the stock and segments of the stock. Thus far, such assessments have only been possible through the use of building-specific BSMs using detailed microdata of the building stock. Moreover, by combining this approach with an agent-based modeling approach to model building stock dynamics, one can track the development of the distributions of parameters over time.

The combination of the BSM and agent-based modeling techniques to develop the ABBSM presented in Papers II and III contributes to the development of modeling of stock dynamics in BSMs. The scientific implications of the developed ABBSM lie in the transition of BSMs from modeling stock dynamics that are based on exogenously defined average rates to the endogenous bottom-up modeling of stock dynamics through ABM techniques. By endogenously modeling stock dynamics through the simulation of adoption and retrofit decisions, the ABBSM can explicitly model the effects of polices that are designed to influence these decisions. Thereby, the ABBSM showcases not only the chosen model adaptation but also the combination of ABMs in BSMs in general. This development paves the way for future connections between BSM-related research and other research fields such as research in energy economics and technology adoption behavior for energy-efficient and renewable energy technologies using ABM. In addition, the use of ABMs to model discrete representations of individual building states, rather than average building archetypes, means that the modeling of building stock dynamics moves away from deterministic modeling to stochastic modeling of stock dynamics. This also has implications for the modeling of stock dynamics in building-specific BSMs, where there is an inherent need for stochastic modeling due to the use of individual buildings.

The use of a BSM to model the long-term stock dynamics of large building portfolios developed in Paper IV offers a new field of application for BSMs. Therefore, this new application of BSMs as a planning tool to study building portfolios allows to further develop BSMs for this purpose beyond maintenance and renovation planning to a more comprehensive assessment of building portfolios for strategic decision-making (e.g., inform decisions to sell and/or demolish buildings). This opportunity may expand BSM-related research to examine the long-term management of building portfolios in the domains of construction and real estate management.

5.3.2 Practical implications

The results of this thesis have some practical implications that are of interest beyond a scientific audience. The assessment of the Swiss residential building stock through a synthetic building stock described in Paper I illustrates the importance of considering the heterogeneity within the building stock when assessing new policies or retrofit strategies. The results indicate that the variation in energy demand and GHG emissions within common stock segments delimitated by building type and construction period can be much larger than the average differences between these segments. A finding that is supported also by empirical studies (Streicher et al., 2018). This variation in energy demand has important implications for devising retrofit and energy-efficiency strategies for certain stock segments because the effectiveness of the measures may considerably vary. Especially since the average assessment results for individual (synthetic) buildings may not be equal to the results of an assessment of the average building state as represented by an archetype building.

The scenario results for the Swiss residential building stock of the ABBSM presented in Papers II and III offer important insights for policy-makers regarding the effect of current and possible future policies for the decarbonization of the Swiss building stock. The results demonstrate the effectiveness of regulatory instruments on the phase-out of fossil fuel-based heating systems. Additional financial incentives (e.g., increase of the CO_2 tax and subsidies) are important to accelerate the transition in the beginning, to prepare the market for the implementation of regulatory instruments, and to decrease an additional financial burden on Swiss building owners owing to the additional investments needed for renewable heating systems and building retrofits.

The results of Paper III indicate that a phase-out of fossil fuel-based heating systems is key to achieve reduction targets for the GHG emissions of the building stock. The results show that while intermediate targets may still be reached, the decarbonization of the stock in the long run can only be achieved through the complete phase-out of fossil fuel-based heating systems. Moreover, to lower the total GHG emissions of the energy used in the building stock, including indirect emissions, the decarbonization of the energy supply of both electricity and district heating is needed as well. Furthermore, the results indicate that owing to slow turnover in the building stock because of long building and component lifetimes, it is important to introduce policies early on to decarbonize the building stock by 2050. This is essential to avoid unwanted lock-in effects (Lucon et al., 2014). For instance, the results reveal that to almost completely phase out fossil-fuel heating systems by 2050, the appropriate policies must be in place by 2025 to make use of the “natural” replacement cycle of heating systems. Otherwise, later interventions will be more expensive because systems and components would have to be replaced or retrofitted before the end of their respective lifetimes. This will result in additional costs for building owners and society because measures cannot be implemented at marginal costs.

The portfolio assessment presented in Paper IV highlights the benefits of taking a strategic approach to maintenance and renovation planning through a lifecycle cost approach. The results indicate that by planning maintenance measures with possible future retrofit measures in mind, one can introduce ambitious retrofit measures to the portfolio with a positive effect on the lifecycle costs of the buildings. Therefore, the results emphasize the benefits of a strategic approach to maintenance and renovation from a portfolio perspective.

6 CONCLUSION

The objective of this thesis was to contribute to the field of building stock modeling with a focus on the modeling of building stock dynamics. The thesis, along with the appended papers, provides a methodology for how the modeling of national building stocks can be further developed in terms of building stock characterization and stock dynamics using an agent-based modeling approach. In addition, BSM is tailored to a new application and addresses building portfolio owners to inform their strategic decision-making and planning of maintenance and renovation measures.

The recent trends in BSM-related research have primarily focused on urban building-specific BSMs, which build upon large microdata sets and 3D city models, to model the building stock (Reinhart and Cerezo Davila, 2016). Studies similar to Streicher et al. (2018) highlight the importance of variation and heterogeneity of the building stock in terms of energy demand and GHG emission of buildings. However, thus far, the assessment of national building stocks has been primarily carried out on average archetype buildings, which limits the study of GHG emissions and energy demand of building stocks to average results. Therefore, by making the assessment of variation possible in the study of national building stocks, the developed methodology for generating synthetic building stocks closes an important gap in the research on building stock modeling. The importance of considering heterogeneity is highlighted by the results of the application for the Swiss residential building stock. These results indicate that the variation of energy demand and GHG emissions within common stock segments of building type and construction period can be much larger than the average differences between these segments.

The trend toward building-specific BSMs developed for urban energy planning has also led to focus on static methods for assessing the status quo. These developments have resulted in a more detailed description of building stocks in these models but have left dynamic BSMs without many changes because the level of detail and computational burden of building-specific BSMs makes the application of dynamic methods more difficult. Thus, modeling approaches for dynamic BSMs still mainly rely on exogenously defined rates to model stock dynamics rather than on modeling the change in the stock endogenously (Sartori, Sandberg, and Brattebø, 2016). This is addressed by the ABBSM developed in this thesis, which makes it possible to model changes in the stock endogenously by modeling retrofit and heating system technology adoption decisions of disaggregated building agents. Compared to other dynamic BSMs, the use of ABM to model decisions on the building level allows to study the effect of specific policies aimed at lowering the building stock energy and GHG emissions rather than assessing only the effect of structural changes in the stock over time. Endogenous modeling of stock dynamics based on the building and component lifetimes also avoids pitfalls such as assuming too high rates of changes including overly optimistic retrofit or diffusion rates.

The ABBSM is validated through the application of the historic development of the residential building stock of Switzerland, which illustrates the suitability of the approach for reproducing aggregate development patterns for retrofit activity, heating system adoption, and energy demand through the modeled decision-making of individual building agents. The application of the model to simulate the future development of the stock assesses the effect of various policies to decarbonize the Swiss residential building stock. The results highlight the effectiveness of regulatory instruments for phasing out fossil fuel-based heating systems while also making the case for financial instruments to prepare the market and lessen the additional burden on building owners during this transition. At the same time, the results suggest that to achieve GHG emission targets of 2050, the relevant policies must be in place by 2030 due to the long replacement cycles of building components. Moreover, the complete decarbonization of the building stock, including indirect emissions, can only be achieved with the simultaneous decarbonization of the energy supply system (i.e., electricity and district heating mix).

Until now, the application of BSMs has been focused on policy advice on urban and national levels as well as on energy planning for cities and districts (Mastrucci, Marvuglia, et al., 2017). Therefore, current modeling approaches are tailored to these applications and focus on characterizing the existing stock to deliver a basis for energy planning and assessing changes in the stock to inform policy-makers. The wider access to building-level data makes BSM applicable to assess large building portfolios but requires an adjustment of modeling approaches to be useful for this application. To make BSM applicable as a portfolio planning tool, the BSM was combined with a methodology for maintenance and renovation planning. The developed model highlights the benefits of taking a strategic approach to maintenance and renovation planning through a lifecycle cost approach, which enables the long-term planning of energy efficiency and GHG emission reduction measures in building portfolios. Therefore, it can support building owners in the development of long-term strategies for the energy demand reduction and decarbonization of their portfolio, which contributes to achieving national energy and climate goals.

7 OUTLOOK

The work presented in this thesis introduces several aspects to the field of BSMs that lay the groundwork for future work and can be expanded upon along different research trajectories.

The generation and modeling of synthetic building stocks, as presented in Paper I, can be further developed and enhanced to improve the generated synthetic buildings and expand the covered scope. A possible further development step is to expand the scope of the covered building types and building uses to cover the non-residential sector and mixed-use buildings. To do this, further development of the building technologies covered by the synthetic stock is needed to cover the range of technologies used in this sector (e.g., cooling systems). Another possible development is to generate spatially distributed synthetic building stocks to differentiate building locations for a region (e.g., cantons in Switzerland or NUTS regions), municipality, or hectare raster level depending on the scale of the application and available data. This may become especially relevant when modeling countries with diverse climate zones because both the energy demand of buildings and the technologies used may differ. Moreover, further research is needed to address some of the shortcomings of the methodology outlined in Section 5.2. For example, additional cross-sectional studies on the building stock may increase understanding of the distributions of and correlations between building characteristics, which will improve the generation of synthetic building stocks.

The generation of synthetic building stocks to include non-residential buildings and the spatial differentiation of the stock can be included in ABBSM developments to expand the scope of the model. By spatially distributing building agents, one may include other aspects of building stock dynamics (e.g., location-specific growth and shrinkage of the stock) in the model by combining it with agent-based land use models such as that of Waddell (2002). Moreover, this development will make it possible to more explicitly consider location-based restrictions and potentials of RESs and other frame conditions (e.g., energy prices and investment costs). In addition, an expansion of the agents covered by the model may further enhance the model's expressiveness. For example, by differentiating among owner types (e.g., private and public landlords), one may introduce owner-specific decision processes and criteria, which would make an owner type-specific assessment of policies possible. Similarly, the model may be further developed by differentiating additional triggers for the retrofitting and replacement of building components (e.g., building owners deciding to renovate after purchasing a new building), which involves a different decision logic compared to that for the replacement of components at the end of their lifetimes. Other already-developed ABMs that are more specific regarding the various adoption processes (e.g., the models of Sopha, Klöckner, and Hertwich (2013) and Friege (2016)) may inform this development, and their decision heuristics may be integrated into the ABBSM. This further development of the decision model applied in the ABBSM should be guided by additional longitudinal studies on the building stock development, which could inform this development and be used to validate the model results. Furthermore, the synthetically created building agents can be combined with a synthetic population to represent various occupant types, which would make it possible to model different occupant behaviors and building-occupant interactions in greater detail (Andrews et al., 2016). Moreover, the scope of diffusion dynamics of the modeled technologies can be expanded upon. Specifically, dynamics in household appliances and lighting are not yet included in the model. Moreover, additional technologies (e.g., photovoltaic systems and connected battery storage) as well as the embodied impact of construction materials and technologies are important for the assessment of the current and future environmental impact of buildings but are currently not covered in the ABBSM.

The use of BSMs for portfolio assessment is still new. Therefore, other functionalities can be envisioned. For example, the optimization of the scheduling of measures given budget constraints and other planning boundaries can be included to facilitate the prioritization of implementation of different measures. In addition, the further development of the BSM as a portfolio planning tool to inform decisions to sell or demolish buildings would make the approach more broadly applicable to strategic decision-making for building portfolios. Moreover, to make the developed method accessible for building owners, one requires a user-friendly interface, and the planning method must be integrated into the company's structure and decision-making processes.

To facilitate the further development of the proposed aspects and possible future developments, the current model implementation should be developed to allow for more flexibility and improved model run times. A shorter model run time will allow to more comprehensively study the sensitivity of the model and uncertainties in its outcomes, similar to Branger et al. (2015) and Mastrucci et al. (2017), which may also inform future development steps.

In the long run, access to microdata on building stocks will probably continue to improve, aided by open access to more administrative data and the development of new data-generation techniques such as remote sensing (Heldens et al., 2017). This, together with data standards on building stock information, such as the CityGML energy ADE (Nouvel et al., 2015), will make data exchange easier. Within this development, BSMs can play an important role in tracking building stocks over time to better understand how building stocks evolve. This will give BSMs a better data basis for the calibration and validation of dynamic models, which will improve their ability to project future development and with it our understanding thereof.

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